Cover_Dries.pdf 1 19/11/15 10:44

BAYESIAN BELIEF NETWORKS IN ECOSYSTEM SERVICE MODELLING

Dries Landuyt

UNIVERSITEIT GENT

FACULTEIT BIO-INGENIEURSWETENSCHAPPEN

Bayesian belief networks in ecosystem service modelling

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2015

ISBN 978-9-0598984-3-1

9 789059 898431

UNIVERSITY press

"To be uncertain is to be uncomfortable, but to be certain is to be ridiculous"

Johann Wolfgang von Goethe (1749-1832)

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UNIVERSITEIT GENT

Faculty of Bioscience Engineering

Bayesian belief networks in ecosystem service modelling

Dries LANDUYT

Ghent, 2015

Thesis submitted in fulfillment of the requirements for the degree of Doctor (PhD) of Applied Biological Sciences

Dutch translation of title:
Bayesian belief networks voor het modelleren van ecosysteemdiensten

Refer to this work as:
Landuyt, D., 2015. Bayesian belief networks in ecosystem service modelling. PhD thesis, Ghent University, Ghent, Belgium

ISBN 978-90-5989-843-1

This study was funded by the Flemish Institute for Technological Research (VITO). Part of the work has been carried out within the ECOPLAN project, funded by the Flemish Agency for Innovation by Science and Technology (IWT), and the ECOFRESH project, funded by the Belgian Federal Science Policy Office (BELSPO).

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Preface

Vier jaar gelezen, gestudeerd, geprogrammeerd, gemodelleerd en geschreven, een boeiende periode waarin ik veel heb bijgeleerd. Peter, jou wil ik dan ook bedanken om me deze kans te geven. Zonder u (en de 'gouden tip' van Charlotte, ook bedankt daarvoor) was ik waarschijnlijk nooit begonnen aan iets wat mij bij nader inzien toch redelijk goed lag. Steven, ook jou ben ik veel dank verschuldigd. Voor je advies, je nuchtere kijk en je 'enthousiasme' als het goed zat. De bemoedigende mails die je sporadisch stuurde, hebben er zeker mee voor gezorgd dat de drive erin bleef. Nog veel doctoraten begeleiden, zou ik zeggen.

Ideeën, methodes en concepten ontstaan en groeien door erover te praten. In het bijzonder wil ik dan ook mijn ugent, vito en ecoplan collega's bedanken. Rob, Sander en Katrien in het bijzonder, jullie ervaring heeft me vier jaar geleden meteen op het juiste pad gezet. Ook Stijn, Joris en Sacha wil ik bedanken voor het delen van hun liefde voor Python, al was ik zonder jullie misschien wel een professional in excel geworden, jammer. De praktische steun mag ook zeker niet onderschat worden, merci daarvoor Sigrid.

Ontspannen was, geloof ik, mijn sleutel tot succes. Merci Frank om me de fiets te leren ontleden. Als het doctoraatsdiploma toch niet zo goed in de markt blijkt te liggen, weet ik wat me te doen staat. Ook merci aan de badmintonners, niets beter dan een pluimke slagen na het werk. Bedankt ook Ruben en Dries, voor jullie kameraadschap en regelmatige dosis onzin. Ook aan de Doornlaners Wies, Hanne, Tomas, Leen, Eva, Dirk en Alma, merci voor de leuke avondjes en weekendjes. Wies in het bijzonder voor je hulp bij het schrijven van mijn eerste paper. Ook aan de Netelanders bedankt om er mee voor te zorgen dat mijn contact met de natuur de afgelopen vier jaar niet beperkt bleef tot het bekijken van cijfers die uit een model rollen.

En uiteraard mag ik ook mijn familie en schoonfamilie niet vergeten. Merci aan de familie Scheelen voor de vele weekendjes die ik in Limburg mocht vertoeven en jullie hulp in het huis en in het bos. Bedankt ook Carmen, mijn grote voorbeeld, ook al heb je voor de landbouw gekozen, en Johan, een betere gesprekspartner causale verbanden kan ik me niet indenken. Moeke, jij ook ontzettend bedankt voor je steun en het uitbaten van 'hotel Vorselaar'. Vake, merci voor alles, leven naar jouw voorbeeld heeft me gebracht waar ik nu ben. Evelien, jij maakt me gelukkig. Merci voor je steun, je vertrouwen, je enthousiasme, je liefde,...

Dries

Gent, 17 november 2015

Summary

The focus of policy makers on economic growth as a proxy for human well-being has had a destructive impact on the global environment. The ongoing global biodiversity loss clearly demonstrates the magnitude of this impact. However, as biodiversity underpins ecological processes that are essential for the earth's functioning, this loss will in the end impact human well-being as well. Increasing evidence shows that, next to economic welfare, the state of ecosystems indeed influences human well-being. To stress the importance of biodiversity for humans, the ecosystem services concept has been introduced. The concept stresses the value of all goods and services that are delivered by the earth's ecosystems and, thus, can be used to incorporate the value of biodiversity in decision making processes.

During the past decades, a broad range of modelling techniques have been applied for ecosystem service modelling and assessment. Although most modelling techniques succeed in estimating local and regional delivery rates for a range of ecosystem services, less attention is being paid to poorly studied services, interactions among services and uncertainties. Bayesian belief network modelling, an established modelling technique in medical diagnosis research and, more general, in machine learning, has the ability to shed more light on these aspects. Bayesian belief networks are semi-quantitative, probabilistic models, can be developed based on a combination of empirical data and expert knowledge and are highly suitable to deal with uncertainties. This study investigates the use of Bayesian belief networks for modelling ecosystem services and assesses whether this modelling technique can add value to current ecosystem service research. The potential of Bayesian belief networks to support decision making, to gain system understanding and to make predictions of the current and future provisioning of ecosystem services are subsequently assessed in the different chapters of this book, both for a small scale case study and for a regional application.

As a first step, a review of the existing literature on the use of Bayesian belief networks to model ecosystem services is carried out. This literature review shows that Bayesian belief networks have been successfully applied to model ecosystem service delivery and that these applications have focussed predominantly on the use of expert knowledge and on participatory modelling. However, the review also shows that the modelling technique is not yet employed at its full potential. Elements that have not yet been fully explored include the use of Bayesian belief networks for cost-benefit analyses, for integrated modelling of multiple services and for large scale regional ecosystem service modelling and mapping.

To assess the potential of the modelling technique for cost-benefit analyses, a model was developed to assess local ecosystem service delivery of a freshwater pond. This case study illustrates the ability of Bayesian belief networks to integrate existing knowledge ranging from empirical data, literature data, existing models and expert knowledge. By applying the model to evaluate alternative pond management practices, also the importance of considering uncertainties becomes clear. The model predictions suggest that uncertainty and risks need to be considered aside from the expected outcome. Based on model outcomes, management practices can be selected that optimize ecosystem service delivery, minimize management costs and that, at the same time, reduce the risk of a negative outcome.

Applying Bayesian belief networks for regional ecosystem service delivery modelling reveals that these graphical models are not only suitable for social learning or to support communication among different scientific disciplines, but can also be used to identify drivers that determine ecosystem service delivery and to quantify interactions among services. The use of Bayesian belief networks to determine interactions among services allows for a more thorough exploration of ecosystem service delivery processes compared to existing techniques.

To be able to map model predictions and to integrate mapping into the model development process, a user-friendly software framework is proposed in Chapter 5. Mapping Bayesian belief network output has been a challenging task due to long model run times, difficulties to visualise uncertainties on maps and due to the absence of links between Bayesian belief network software and geographical information software (GIS). The open-source plug-in for Quantum GIS, which was developed during this thesis, tackles these challenges and offers a user-friendly framework for mapping the provisioning of ecosystem services and associated uncertainties. Besides, the plug-in can be used in a range of other research domains that deal with uncertainties and spatial data.

As a final step, the ability of Bayesian belief networks to model future ecosystem service delivery was assessed. For this assessment on the scale of Flanders, Bayesian belief network models were coupled with a cellular automaton model that predicts land use change in Flanders. Depending on the socio-economic development scenario and the service considered, both increases and decreases in ecosystem services can be expected in the future. The main advantage of the use of Bayesian belief networks in this context is the ability to propagate uncertainty from one model component to the other. Analysing this uncertainty propagation learns that the uncertainty attached to the ecosystem service delivery models is more important than the uncertainty associated to land use allocation. However, accounting for land use allocation uncertainty will become more important when ecosystem service delivery models evolve and their predictions will become less uncertain.

The applications of Bayesian belief networks in this study are promising and show that the modelling approach can contribute to ecosystem service research in Flanders. The models can, for example, increase the transparency of the research and can aid in studying interactions among services. However, to obtain spatially explicit estimates for Flanders, more complex modelling approaches that are able to account for spatial interactions are likely more suitable. Bayesian belief networks are more suitable for applications where less knowledge is available and where uncertainties are dominant and can influence decision-making considerably.

Samenvatting

De focus van beleidsmakers op economische groei als indicator voor welvaart heeft een destructieve impact op het milieu, geïllustreerd door de continue achteruitgang van de globale biodiversiteit. Aangezien biodiversiteit de basis is van vele natuurlijke processen die het functioneren van de aarde bepalen, zal deze achteruitgang op lange termijn eveneens een impact hebben op het menselijk welzijn. Meer en meer studies tonen aan dat naast economische groei ook de staat van ecosystemen het menselijk welzijn beïnvloeden. Om het belang van biodiversiteit te benadrukken, werd het ecosysteemdiensten concept ingevoerd. Dit concept, dat duidt op de voordelen die ecosystemen leveren (zowel goederen als diensten), kan gebruikt worden om de waarde van biodiversteit mee te nemen in beleidsbeslissingen.

De afgelopen jaren zijn er verschillende modellen ontwikkeld die het mogelijk maken de levering van ecosysteemdiensten te onderzoeken. Hoewel deze modellen erin slagen de levering van verschillende ecosysteemdiensten te voorspellen en te analyseren, besteden zij minder aandacht aan onzekerheden, weinig bestudeerde ecosysteemdiensten en interacties tussen diensten. Bayesian belief netwerk modellering, een recent geïntroduceerde innovatieve modelleertechniek, biedt echter de mogelijkheid deze facetten beter te belichten. Bayesian belief netwerk modellen zijn grafische, probabilistische modellen die zowel op basis van data als op basis van expertkennis ontwikkeld kunnen worden en daarnaast zeer efficiënt kunnen omgaan met onzekerheden.

Deze studie onderzocht het gebruik van Bayesian belief netwerk modellen voor het modelleren van ecosysteemdiensten in Vlaanderen en bekeek hoe Bayesian belief netwerk modellen een toegevoegde waarde kunnen hebben voor het ecosysteemdienstenonderzoek in Vlaanderen. In deze studie werd de capaciteit van Bayesian belief netwerk modellen voor het ondersteunen van beleidsbeslissingen, voor systeemanalyse en voor het voorspellen van de huidige en de toekomstige levering van eco-

systeemdiensten onderzocht, zowel voor kleinschalige toepassingen als voor toepassingen op regionaal niveau.

Allereerst werd op basis van een literatuurstudie onderzocht hoe Bayesian belief netwerk modellen momenteel gebruikt worden voor het modelleren van ecosysteemdiensten. Uit deze literatuurstudie blijkt dat Bayesian belief netwerk modellen reeds succesvol werden toegepast in dit onderzoeksdomein en dat deze toepassingen voornamelijk focusten op het gebruik van expertkennis en het betrekken van stakeholders doorheen het gehele modelleerproces. De literatuurstudie toonde echter eveneens aan dat het potentieel van de modelleertechniek momenteel nog niet ten volle benut wordt. Aspecten die te weinig aan bod komen zijn onder andere het gebruik van Bayesian belief netwerk modellen voor het modelleren van verschillende diensten en de interacties tussen deze diensten, het gebruik van Bayesian belief netwerk modellen voor kosten-baten analyses en voor het modelleren en karteren van ecosysteemdiensten op regionaal niveau.

Een eerste facet dat onderzocht werd, is het gebruik van Bayesian belief network modellen voor kosten-baten analyses waarbij ecosysteemdiensten in beschouwing worden genomen. Het toepassen van deze techniek op een vijver systeem illustreert de capaciteit van de modelleertechniek om allerhande kennis bij elkaar te brengen en te integreren in één model. De evaluatie van alternatieve beheersvormen aan de hand van het ontwikkelde model illustreert eveneens het belang van het in beschouwing nemen van onzekerheden in een kosten-baten analyse. Om optimale beslissingen te nemen moeten onzekerheden in beschouwing genomen worden naast de verwachte baten. Enkel zo kunnen beheersvormen geselecteerd worden die de levering van diensten optimaliseren, de beheerskosten minimaliseren en tegelijkertijd het risico op negatieve baten beperken.

Het toepassen van Bayesian belief netwerk modellen voor het modelleren van ecosysteemdiensten op regionaal niveau toont aan dat Bayesian belief netwerk modellen niet alleen geschikt zijn voor het samenvatten van de huidige kennis en het ondersteunen van partcipatieve processen, maar ook gebruikt kunnen worden voor het identificeren van sleutelvariabelen die instaan voor de levering van bepaalde diensten en voor het kwantificeren van interacties tussen diensten. Vergeleken met de bestaande technieken om interacties tussen diensten te analyseren, biedt de in dit doctoraat voorgestelde methode aan de hand van Bayesian belief netwerk modellen meer mogelijkheden voor een grondige systeemanalyse.

Om het karteren van modelvoorspellingen mogelijk te maken en kartering beter te integreren in het modelontwikkelingsproces, werd een gebruiksvriendelijk software raamwerk ontwikkeld. Kartering van Bayesian belief network output is uitdagend omwille van de relatief lange rekentijd van de modellen, omwille van moeilijkheden bij het karteren van onzekerheden en omwille van het ontbreken van een koppeling tussen Bayesian belief netwerk software en geografische informatie software (GIS). De in deze studie ontwikkelde plug-in voor Quantum GIS biedt een oplossing voor deze uitdagingen en maakt het mogelijk op een eenvoudige manier ecosysteemdiensten te karteren tezamen met de onzekerheden op deze voorspellingen. De tool kan zowel gebruikt worden binnen het ecosysteemdiensten onderzoek als in andere onderzoeksdomeinen die frequent te maken hebben met ruimtelijke data en onzekerheden.

In het voorlaatste hoofdstuk van dit doctoraat wordt dieper ingegaan op het gebruik van Bayesian belief netwerk modellen voor het voorspellen van de toekomstige levering van ecosysteemdiensten in Vlaanderen. Hiervoor werden de ontwikkelde modellen gekoppeld met een model dat landgebruiksveranderingen voorspelt voor verschillende toekomstscenarios voor Vlaanderen. De voorspellingen zijn niet eenduidig en geven aan dat zowel dalingen als stijgingen in de levering van ecosysteemdiensten te verwachten zijn, afhankelijk van het scenario en de beschouwde dienst. Het gebruik van Bayesian belief netwerk modellen maakt het eveneens mogelijk onzekerheden te propageren van het ene model naar het andere. De analyse van deze onzekerheidspropagatie toont aan dat de onzekerheden van het landgebruiksmodel weinig invloed hebben op de onzekerheid van de toekomstige levering van ecosysteemdiensten. Naarmate ecosysteemdienstenmodellen evolueren en hun voorspellingen minder onzeker worden, kan het in beschouwing nemen van de onzekerheid van landgebruiksvoorspellingen echter belangrijker worden.

De toepassingen van Bayesian belief netwerk modellen binnen dit doctoraat zijn veelbelovend en tonen aan dat de modelleertechniek wel degelijk kan bijdragen aan het ecosysteemdienstenonderzoek in Vlaanderen. Zo kan de modelleertechniek de transparantie van het onderzoek verhogen en bijdragen aan het onderzoek naar interacties tussen diensten. Voor het bekomen van ruimtelijk expliciete schattingen op het niveau van Vlaanderen lijkt het gebruik van complexere modeltypes, die eveneens ruimtelijke interacties in beschouwing kunnen nemen, echter meer voor de hand te liggen. Bayesian belief netwerk modellen lijken voornamelijk geschikt te zijn voor toepassingen waar minder kennis voorhanden is en waar onzekerheden dominant zijn en het beslissingsproces sterk kunnen beïnvloeden.

Contents

List of abbreviations

API	application programming interface
ARIES	Artificial Intelligence for Ecosystem Services
BBN	Bayesian belief network
BDN	Bayesian decision network
CA	cellular automaton
CBA	cost-benefit analysis
CBD	Convention on Biological Diversity
CDF	cumulative probability distribution
CE	choice experiment
CICES	Common International Classification of Ecosystem Services
CPT	conditional probability table
DAG	directed acyclic graph
DBN	dynamic Bayesian network
EEA	European Environmental Agency
ECOFRESH	Ecosystem Services of Freshwater Systems
ECOPLAN	Planning for Ecosystem Services
EFF	extensive fish farming
ES	ecosystem service
EU	European Union
GE	global economy
GIS	geographic information system
GISCAME	Geographic Information System, Cellular Automaton, Multicriteria Evaluation
GUMBO	Global Unified Metamodel of the Biosphere
IFF	intensive fish farming
InVEST	Integrated Valuation of Ecosystem Services and Trade-offs
IPBES	International Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change

MEA	Millennium Ecosystem Assessment
MERIT	Management of the Environment and Resources using Integrated Techniques
MPS	most probable state
NCM	nature conservation management
OOBN	object oriented Bayesian network
PM_{10}	particulate matter up to 10 μm
$PM_{2.5}$	particulate matter up to 2.5 μm
PMPS	probability of the most probable state
PPCI	posterior probability certainty index
QGIS	Quantum GIS
RC	regional communities
SE	strong europe
SOC	soil organic carbon
SolVES	Social Values for Ecosystem Services
SWOT	strengths, weaknesses, opportunities and threats
TEEB	The Economics of Ecosystems and Biodiversity
TESSA	Toolkit for Ecosystem Service Site-based Assessment
TEV	total economic value
TM	transatlantic market
VITO	Vlaamse Instelling voor Technologisch Onderzoek
VMM	Vlaamse Milieumaatschappij
VR	variance reduction
WTP	willingness-to-pay
WTO	World Trade Organisation

1 General introduction

The focus of policy makers on economic growth as a proxy for human well-being has had a destructive impact on the global environment. The ongoing global biodiversity loss clearly demonstrates the magnitude of this impact (Secretariat of the Convention on Biological Diversity, 2010). However, as biodiversity underpins ecological processes that are essential for the earth's functioning, this loss will in the end impact human well-being as well. Increasing evidence shows that, next to economic welfare, the state of ecosystems indeed influences human well-being (e.g. Costanza et al., 1997; MEA, 2005; TEEB, 2010). Examples include wetlands that store surface water and reduce downstream flood risks (Broekx et al., 2010), forests where people can recreate in and that have positive health impacts (Hermy et al., 2008) and dry dune soils that infiltrate and filter water that can be abstracted as drinking water elsewhere (Batelaan and De Smedt, 2001). Although negative effects of biodiversity loss on human well-being are less pronounced in the rich countries of the Western world, developing countries are already experiencing the impact (e.g. excessive erosion, floods, pests threatening food production). To stress the importance of biodiversity for humans, the ecosystem services concept has been introduced. The concept stresses the value of all goods and services that are delivered by the earth's ecosystems and, thus, can be used to incorporate the value of biodiversity in decision making processes. Eventually, the concept aims at supporting sustainable management of natural resources to enhance the well-being of current and future generations.

1.1 The ecosystem services concept

Although the capacity of nature providing benefits was already observed in ancient times, the ecosystem services (ES) concept, to stress the ability of nature's functions to improve human well-being, founds its origin in the literature from the late 1970's (Gómez-baggethun et al., 2010). Pioneering publications by Schumacher (1973) and Westman (1977) stressed the importance of nature and associated biodiversity by using the terms 'natural capital' and 'nature's services'. The major aim of these early publications was to change the public opinion towards biodiversity conservation. Recently after, Ehrlich and Ehrlich (1981) were the first to use the term 'ecosystem services'. Ehrlich and Mooney (1983) were the first to mention the concept in scientific literature. Later, in the 1990's, numerous ES related papers (e.g. Daily, 1997) led to the mainstreaming of the concept in the scientific literature. The paper of Costanza et al. (1997), in particular, led to both a rise in studies that value ES in monetary terms and discussions on the sense and non-sense of monetary valuation. Meanwhile, also political attention was rising, starting with the Convention on Biological Diversity (CBD), established in 1992 as a response to global biodiversity loss (Gómez-Baggethun and Ruiz-Pérez, 2011). Parallel to the activities of the convention, two international scientific initiatives tried to assess the impact of biodiversity loss on human well-being: the Millennium Ecosystem Assessment (MEA) in 2001 and The Economics of Ecosystems and Biodiversity (TEEB) in 2007. Both initiatives aimed to provide scientific input to the CBD. The MEA report (MEA, 2005) discusses the state of the world's ecosystems, the predicted ecosystem changes and the effect of these changes on human well-being. It can be seen as the first scientific report that brought the ES concept into the policy arena (Larigauderie and Mooney, 2010). In 2010, TEEB published a report that assessed the monetary cost of declining ES delivery due to global biodiversity loss. As a follow-up of the MEA, the international community established the International Platform on Biodiversity and Ecosystem Services (IPBES) in 2012 to strengthen the science-policy interface. Today, the importance of ES is still growing, both in science and policy. The EU biodiversity strategy 2020, a strategy that represents the EU commitments made in the context of the CBD, is an example of how ES are currently being integrated in policy documents. ES assessment and mapping is included as an important task that has to be performed by all EU member states.

Table 1.1: Proposed definitions of the ecosystem services concept (adapted from Nahlik et al. (2012)).

Definition	Reference
- the benefits human populations derive, directly or indirectly, from ecosystem functions	Costanza et al. (1997)
- the conditions and processes through which natural ecosystems, and the species that make them up, sustain and fulfil human life	Daily (1997)
- the capacity of natural processes and components to provide goods and services that satisfy human needs, directly or indirectly	de Groot et al. (2002)
- the set of ecosystem functions that is useful to humans	Kremen (2005)
- the benefits people obtain from ecosystems	MEA (2005)
- components of nature, directly enjoyed, consumed, or used to yield human wellbeing	Boyd and Banzhaf (2007)
- the aspects of ecosystems utilized (actively or passively) to produce human wellbeing	Fisher et al. (2009)
- a range of goods and services generated by ecosystems that are important for human wellbeing	Nelson et al. (2009)
- benefits that humans recognize as obtained from ecosystems that support, directly or indirectly, their survival and quality of life	Harrington et al. (2010)
- a collective term for the goods and services produced by ecosystems that benefit humankind	Jenkins et al. (2010)
- direct and indirect contributions of ecosystems to human wellbeing	TEEB (2010)

1.2 Making the ecosystem services concept operational

1.2.1 Defining the ecosystem services concept

The first widely recognised definition of ES defines ES as the benefits people obtain from ecosystems (MEA, 2005), in which ecosystems are defined as a community of living organisms in conjunction with their abiotic environment. Alternative definitions and interpretations are given in Table 1.1 (adapted from Nahlik et al. (2012)). The proposed definitions differ notably in the way they link services to benefits for human well-being. ES can be defined as the processes that generate benefits or as the benefits themselves. Although stressing only the benefits facilitates the identification of individual ES, it may lead to the ignorance of several important background processes and functions (e.g. biodiversity) that aren't benefits themselves, but are crucial for the delivery of benefits. Current debates on the difference between functions, services and benefits and the broad set of definitions that result from it can be problematic as pointed out by several scientists (e.g. Seppelt et al., 2011). Ambiguous definitions may, for example, give rise to differences between what ecologists measure in the field and what economists and sociologists value (Nahlik et al., 2012).

Recently, more and more scientists argue that also disservices, defined as functions of ecosystems that are perceived as negative for human well-being (Lyytimäki and Sipilä, 2009), need to be considered in ES assessments. Only considering benefits while ignoring potential costs might decrease the credibility of ES assessments. Moreover, not considering disservices might lead to suboptimal management strategies, especially in urban contexts (Lyytimäki and Sipilä, 2009). Examples of disservices include the spread of human diseases and the presence of harmful insects in urban areas or undesired plant species in agricultural fields. These disservices can be produced through anthropogenic (suboptimal management) or natural drivers (Dunn, 2010). Although the amount of papers published on disservices is increasing, systematic studies on disservices are currently still rare (von Döhren and Haase, 2015). As a consequence, clear suggestions on how to implement or integrate the concept in ES assessments and clear definitions of the concept still need to be formulated. As stated by von Döhren and Haase (2015), most studies define disservices as adverse outcomes of ecological change or as suboptimal ES delivery due to biodiversity loss. These definitions suggest that there is a thin line between disservices and the more frequently applied concept of trade-offs. In contrast to disservices, trade-offs focus on the fact that negative ES delivery rates often coincide with positive delivery rates of other services and that finding the optimal balance is the key challenge. Throughout this thesis, the focus will be on modelling services and trade-offs rather than disservices.

1.2.2 Unravelling the production chain of ecosystem services

To disentangle the relationships between ecosystems, processes, functions and services, Haines-Young and Potschin (2010) developed a conceptual framework that clearly visualises these concepts and the links among them. Their so-called 'ES delivery cascade' resembles a production chain and clearly visualises the fact that benefits flow from services, services from functions, functions from processes and processes from the biophysical structure of the ecosystem. Ecosystem functions are defined as biophysical processes that may be potentially useful. If the function is perceived useful, in a particular socio-economic context, the function will become a service. Thus, an ES is defined as an output of an ecosystem that directly leads to a benefit. Although this definition does not exactly correspond to the ones originally proposed by Costanza et al. (1997) and MEA (2005), it does acknowledge that there is a close link between ecosystem services and direct benefits for human well-being. Note that the represented arrows in the conceptual scheme are not necessarily one-to-one relationships. Several services can lead to one benefit and one service may

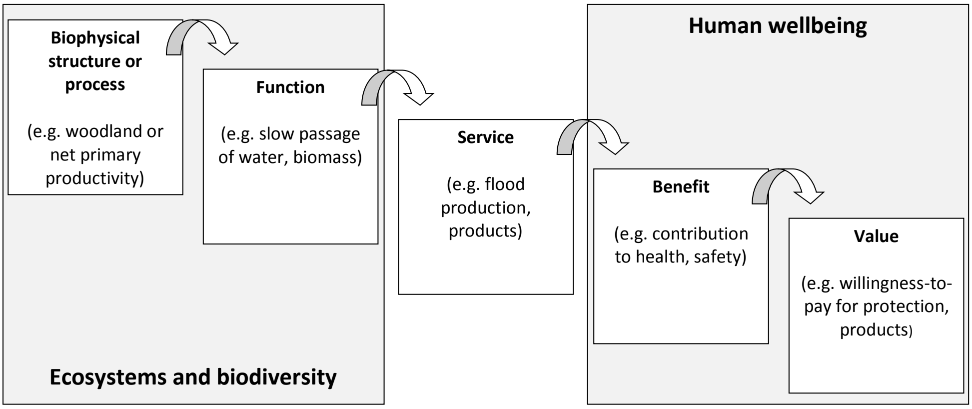


Figure 1.1: The ecosystem services 'cascade' representing ecosystem service delivery as a production chain. In each box, examples are provided to illustrate the concepts. Woodlands slow down runoff. Slow passage of water can cause a decrease in flooding events which will contribute to human well-being by increasing the feeling of safety. The value of this increased well-being can be expressed in monetary terms (adapted from Haines-Young and Potschin (2010)).

lead to several benefits.

As can be seen in Figure 1.1, biodiversity and ES are represented as two distinct elements. As biodiversity determines the biophysical structure of the ecosystem, the ES cascade regards biodiversity as an aspect that underpins the delivery of ES. In reality, however, this link is not always that clear (Cardinale et al., 2012). For some services, there is a clear link with species presence: trees will ensure wood production, beavers will improve flood protection through water retention and bees will ensure crop pollination. In most cases, however, ES provision is determined predominantly by the presence of specific habitats rather than by the presence of specific species. Thus, there is not always a direct causal relation between biodiversity and ES. Nevertheless, correlations are often found (e.g. Schneiders et al., 2012).

The cascade representation also illustrates the need to integrate multiple scientific disciplines by visualising the different steps of the ES assessment process. Biophysical structures need to be defined and delineated, the ecosystem's production of functions and services needs to be modelled and, as a final step, the services, those that directly lead to societal benefits, can be valued either in monetary or non-monetary terms taking into account the socio-economic context. While ecological studies can be used to quantify relations between biophysical structures and functions, socio-economic studies are needed to translate services into benefits and values. These different steps are, however, not always considered. Approaches exist that directly link biophysical structures to societal values without considering the intermediate mechanisms (e.g. Costanza et al., 1997). In this thesis, however, the aim is to model the full production chain by using the cascade representation as a starting point to construct ES models.

1.2.3 Classification of ecosystem services

A consistent typology is an important step towards a clear definition and a common understanding of indicators to quantify ES delivery. The MEA (2005) was the first to propose a typology for ES and suggested four main classes: supporting, regulating, provisioning and cultural services. They also defined the link between their broad service categories and human well-being. Regulating, provisioning and cultural services had a direct impact on human well-being, while supporting services, which only support the delivery of other services, had an indirect impact. An important aspect of this classification is that biodiversity is not seen as a service itself but as something that underpins the delivery of services.

Several authors argue that the MEA classification, which classifies supporting services on the same level as the other service categories mixes up 'ends' with 'means' and that this may give rise to double counting in ES assessments (e.g. Boyd and Banzhaf, 2007; Wallace, 2007). In their papers, Boyd and Banzhaf (2007) and Wallace (2007) suggest alternative typologies and promote their use in future research. However, others suggest that there is no one-size-fits-all solution and suggest that the applied typology should be chosen depending on the aim of the study (Costanza, 2008; Fisher and Turner, 2008). In line with this belief, several classification systems have been proposed for specific cases. Costanza (2008), for example, proposes a classification of ES based on spatial characteristics, while de Groot et al. (2002) propose a classification specifically intended for use in valuation studies.

Recently, the European Environment Agency (EEA) initiated a study to develop a standardised typology, called CICES (or Common International Classification of Ecosystem services) to support ES accounting studies. This classification was based on previous accounting work of the EEA and further developed through several successive consultations of the international community. Important aspects of this classification system include the emphasis on final services, the exclusion of abiotic ecosystem outputs and the hierarchical structure of the classification system. To avoid double counting issues, the classification system focusses on final ES and de-

Table 1.2: The CICES-BE classification limited to the group level. Individual services, in CICES listed as classes or subclasses, are not included here (based on Turkelboom et al. (2014)).

Section	Division	Group
Provisioning	Nutrition	Biomass
		Potable water
	Materials	Biomass
		Non-potable water
	Energy	Biomass-based energy sources
Regulation and maintenance	Mediation of waste, toxics and other nuisances	Soil and water quality regulation
		Air quality regulation
		Shielding
	Mediation of flows	Mass flow
		Liquid flow
	Maintenance of physical, chemical and biological conditions	Life cycle maintenance, habitat and gene pool protection
		Pest and disease control
		Soil formation and composition
		Atmospheric composition and climate regulation
Cultural	Physical and intellectual interactions with biota, ecosystems and land- and seascapes	Natural environment suitable for outdoor activities
		Spiritual, symbolic and other interactions with biota, ecosystems and land- and seascapes
		Natural surroundings of built-up areas
		Spiritual and/or emblematic

fines them as the biotic outputs of ecosystems that are used as inputs (together with other types of capital) to create ecosystem goods and services. This definition is in accordance with the ES cascade framework (Figure 1.1). Specifically for Belgium, an adaptation of the CICES classification has been proposed by Turkelboom et al. (2014). While the main categories (sections and divisions) were kept to ensure comparability with international research, several, in the Belgian context, important ES were added. Furthermore several class names were adapted in accordance with the comments that came out of the consultation of Belgian experts and practitioners. The adapted classification, also referred to as CICES-BE, is provided in Table 1.2. As this thesis focusses on Belgian case studies, the CICES-BE classification is used as the reference classification throughout this book.

1.3 The state-of-the-art of ecosystem service assessment

During the last decades, a broad range of models to predict ES delivery have been developed (for an overview see Seppelt et al. (2011) and Crossman et al. (2013)). The general aim of these models is to inform and support environmental decision making. They are able to quantify, for example, to what extent land use change may alter ES delivery or to what extent ecosystem characteristics influence ES production. Due to the social dimension of the ES field, ES models may also play an important role in supporting social learning (Holzkämper et al., 2012). Models designed for social learning allow individuals to experiment with the model to help them understand the behaviour of a system (Kelly (Letcher) et al., 2013).

Aside from these different aims, the diversity of models being used is driven by the diversity of endpoints being modelled (Crossman et al., 2013). These endpoints can be functions, services, benefits or proxies for the delivery of a particular ES, such as, soil organic carbon storage as a proxy for climate regulation and number of visits or overnight stays as a proxy for recreation. In case the model endpoints are benefits, economic models are frequently applied (e.g. Broekx et al., 2013b), in case functions or services are assessed, ecological models, generally based on field data, are suited the most (e.g. Meersmans et al., 2008).

The diversity of services being modelled is a final reason for the diversity of models being used (Crossman et al., 2013). Some services are easily measurable, can be evaluated in the field and can be modelled using conventional data-driven ecological modelling techniques. Most of the cultural services, on the other hand, are less easily measurable in the field and need to be assessed trough interviews, questionnaires or participatory approaches. Economic and social modelling approaches are needed to handle this kind of data. Differences in measurement techniques lead to differences in data types and, hence, to differences in modelling approaches being used (Smith et al., 2011).

The following paragraphs provide a generic overview of modelling techniques that are currently being used in the ES modelling domain and highlight their main characteristics and shortcomings.

1.3.1 An overview of modelling techniques

Four broad categories of models can be distinguished according to the amount of data needed to develop and run the model, the complexity of the model and the knowledge base used to develop the model (Figure 1.2).

A first category of models are models with a low complexity level and that are solely based on expert knowledge, referred to as 'expert-based look-up tables' in Figure 1.2. Usually these models are developed based on knowledge from a selected group of experts that score the suitability of a set of land use/land cover types to deliver ES (e.g. Burkhard et al., 2009). The major advantage of this approach is that they can be used for rapid ES assessments without having to spend money and time in expensive data gathering campaigns and subsequent modelling work. Disadvantages of the approach are the subjective nature (although objective confidence indicators exist (Jacobs et al., 2015)) and the inability of these land use based approaches to account for auxiliary variables, such as, soil type and hydrology (Martínez-Harms and Balvanera, 2012).

A second category of models are those that are based on a small amount of data or a set of key figures, gathered at a specific site but that are assumed to be generally applicable to obtain rough estimates of ES production. This group of models can be referred to as 'data-based look-up tables'. Extrapolation of data is carried out by using a look-up table that links a range of land use types to the available data on ES delivery (or a proxy for ES delivery). This method has, for example, been applied to model ES delivery on a global scale using a look-up table that associates monetary values to land use types (Costanza et al., 1997).

The third category of models consists of more complex models that make use of a range of spatial data layers to analyse the delivery of ES (e.g. Kareiva et al., 2011), an approach referred to as the ecological production function approach by Nemec and Raudsepp-Hearne (2013). These models are generally developed based on well-known causal relationships between ecological and social variables (Martínez-Harms and Balvanera, 2012). In this thesis, the term 'GIS models' is used as general term to refer to this subset of models. GIS refers to Geographical Information Systems or systems that make use of spatial data layers and that explicitly consider the spatial locations of features. These models are generally not site-specific as they are based on general knowledge and established biological, ecological and economic principals. Hence, developed models can be easily transferred to other case studies in case the necessary spatial data sets are available (Smith et al., 2011). The approach also offers ways to integrate spatial interactions, for example, among supply and demand zones (Adamowicz et al., 2011). However, due to lacking data for model validation, models are generally not validated. This often lowers end-users' confidence in the model outcome.

A final category of models are those purely based on empirical data, referred to as

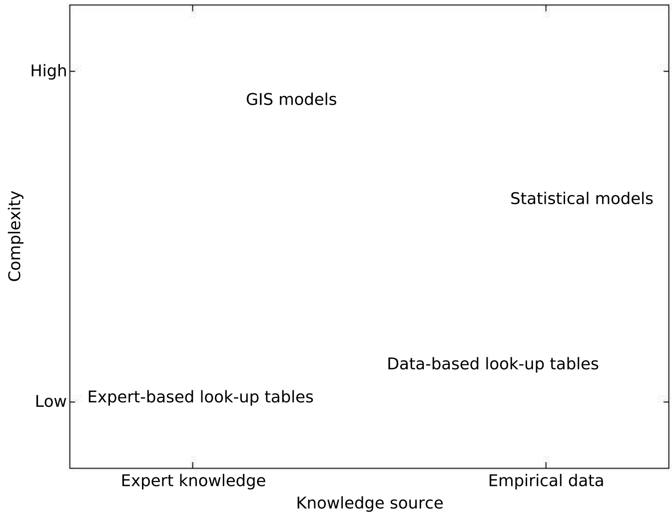


Figure 1.2: A framework to classify ecosystem service modelling approaches according to the complexity of the model and the knowledge base used to develop the model.

'statistical models' in Figure 1.2. These data can be obtained through sampling campaigns or questionnaires. Although most of these statistical models are aspatial, some exceptions exist. In case predictor variables are included that can be represented spatially, model results can be spatially extrapolated. Spatially explicit usage of statistical models, such as, linear regression models and generalised linear models have been described by Meersmans et al. (2008) and Kienast et al. (2012), respectively. A statistical modelling approach is generally regarded as the most desirable way to model ES delivery (Martínez-Harms and Balvanera, 2012; Eigenbrod et al., 2010) as it may provide strong insights that are statistically defensible, however, limited availability of data often impedes applying these models for a broad set of services. Moreover, these models' strong dependence on field data may impede extrapolation of their results to case studies outside the region of data collection (Smith et al., 2011).

1.3.2 The valuation step

ES valuation, the final step in the ES cascade, is mostly performed to trade off impacts on different services or to compare impacts with other impacts such as investment costs or economic revenues created by infrastructure projects (e.g. installation of controlled floodplains, extension of the road network). Valuation can be carried out either in monetary or in non-monetary terms. Non-monetary values of ES can be obtained by consulting stakeholders through surveys, interviews or participatory processes (e.g. Howarth and Wilson, 2006). The suitability of a particular valuation approach will largely depend on the context and aim of a study. Building on the available knowledge in Flanders, this thesis will predominantly focus on monetary valuation that attempts to estimate the instrumental value of ES, also referred to as the total economic value or TEV. Note that this monetary value differs from the intrinsic value of an ecosystem. Although monetary valuation is often contested (e.g. Gómez-Baggethun and Ruiz-Pérez, 2011; Spangenberg and Settele, 2010), it offers several advantages, including the ability to carry out cost-benefit analyses and the ability to communicate the importance of biodiversity in a language that speaks to dominant economic and political views (Kumar et al., 2013) and that can be understood by the general public. As the lack of monetary values for ES has been mentioned as one of the main causes of ecosystem degradation and biodiversity loss in the past (TEEB, 2010), monetary valuation studies may support the conservation of ecosystems.

Although integrating the valuation step in the models described above is nothing more than assigning a value to a modelled biophysical quantity or to a specific ecosystem, the real challenge is to choose a proper valuation technique to come up with this value. A broad range of valuation approaches are available and can be classified into market price methods, stated preference methods and revealed preference methods. Most of them are statistical techniques that are developed based on data gathered through questionnaires and interviews (stated preference methods), observations of human behaviour (revealed preference methods) or market price analyses (market price methods) (TEEB, 2010). These valuation techniques are either used as stand-alone statistical models or to extract values that can be integrated in other modelling techniques. Market price methods are mostly used to value provisioning ES that are directly or indirectly traded in real markets (e.g. food production) or to value ES that lead to real costs when they are not being delivered (e.g. water quality regulation, air quality regulation). Revealed preference methods are based on observations of human behaviour. They estimate, for example, the monetary value of a recreational site based on the distance visitors travel to reach that site (e.g. Hanley and Barbier, 2009). A drawback of this approach is that only use values are accounted for. To be able to grasp non-use values as well, stated preference methods can be used. They derive ES values based on questionnaires

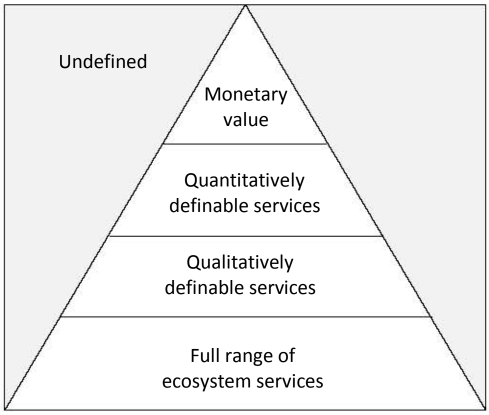


Figure 1.3: Due to limited system understanding, only for a few ecosystem services monetary values can be estimated. The valuation pyramid visualises the steps towards monetary valuation and the sequential drop out of services towards the top of the pyramid (Kettunen et al., 2009).

that directly ask people about their opinion on the value of a service. Various stated preference methods exist, ranging from questionnaires that directly ask for monetary values (e.g. Loomis et al., 2000), referred to as contingent valuation approaches, to questionnaires that derive monetary values indirectly through proposing a range of alternatives the respondents needs to choose from (for more information on choice experiments see the work of Hoyos (2010)).

The ease of obtaining these monetary values entails risks as well. As the obtained monetary values can be summed up, the outcome of monetary valuation studies can be easily interpreted by decision makers which might have the impression that the provided numbers represent the total value of an ecosystem. Monetary values can therefore be misleading and even dangerous when they are used to simplify the complexity of an ecosystem to one single monetary value (Spangenberg and Settele, 2010). First of all, as mentioned above, economic values only represent a small part of the total value of an ES which includes ecological and social values as well (Dendocker et al., 2014). Secondly, not all ES can be valued monetarily. Only for a limited set of services, the necessary techniques and data are available to model the full cascade and to eventually obtain monetary values. The valuation pyramid, presented in Figure 1.3, clearly visualises this phenomenon.

The key is to frame the output of your research in order to avoid misuse, clearly indicating which aspects of a service you consider and which aspects you monetise in the end. To fully inform decision makers, information on monetary values should be complemented with information on other value types, information on expected biodiversity levels and quantitative and qualitative information on services that cannot be monetised.

1.3.3 Integrated tools

Although being essentially two successive steps in the ES production cascade, ES valuation and biophysical modelling studies are often carried out independently. However, several integrated tools have been developed that attempt to integrate both aspects for a range of services. These tools are generally developed as web-based applications, stand-alone software packages or GIS plug-ins. They generally have the capacity to predict the delivery of multiple services, to generate maps of ES delivery and to analyse several alternative land management scenarios. The idea behind these tools is that the methodologies incorporated in the tool can be transferred to other regions if site-specific input data (usually spatial data) are available.

Integrated Valuation of Ecosystem Services and Trade-offs or InVEST (Kareiva et al., 2011) is internationally one of the most applied (and advertised) tools to model ES delivery. InVEST incorporates a broad range of modelling types, ranging from simple look-up tables to complex GIS models. Another example, specifically developed for the Flemish context, is the Nature Value Explorer (Broekx et al., 2013b). It is a web-based application that offers users the possibility to estimate the benefits that are associated to user-defined nature restoration scenarios. The tool is to a large extent based on Flemish data and is therefore suitable for decision-making in Flanders.

Aside from InVEST and the Nature Value Explorer, a broad range of other tools have been developed during the last decades (e.g. ARIES (Bagstad et al., 2011), GISCAME (Koschke et al., 2012), TESSA (Peh et al., 2013), SolVES (Sherrouse et al., 2011), GUMBO (Boumans et al., 2002), MIMES (Boumans and Costanza, 2015)). The tools mainly differ in terms of the intended end-user group, the amount of data that is needed to run the tool and which decision-making questions they can solve (Waage and Stewart, 2008). For a detailed comparison among tools, see also Peh et al. (2013); Bagstad et al. (2013); Nelson and Daily (2010) and Nemec and Raudsepp-Hearne (2013).

1.3.4 Shortcomings and challenges

While there's no doubt that the high diversity of models has contributed to a better understanding of ES delivery processes and better ES accounts, both under data-poor and data-rich circumstances, it has also made the ES research field a scattered research field (Seppelt et al., 2011). The available knowledge is scattered and encapsulated in models, empirical data, expert knowledge, scientific publications and technological reports. Comparing different studies that model different services to analyse trade-offs and synergies among services has become difficult. Unfortunately, a common framework or modelling approach that has the capacity to integrate these different types of data and knowledge, all with another degree of uncertainty attached to it, is still missing. Such integrated models (defined as models that integrate multiple processes, services and disciplines (Kelly (Letcher) et al., 2013) can be very useful to assess trade-offs and synergies among the production processes of multiple services.

As ES delivery processes exceed the boundaries of individual disciplines, knowledge needs to be integrated across disciplines as well. Proper integration of multiple disciplines is frequently impeded by the existing mismatch between biophysical models and valuation approaches and between what is usually modelled in ecological research (stocks and flows) and what is usually valued in economic research (marginal changes) (Nemec and Raudsepp-Hearne, 2013). Also in this context, a common framework would be useful to integrate the different steps of the ES cascade.

Another important shortcoming of most ES models, unrelated to the previous ones, is ignorance of uncertainty although they may play an important role in decision making (Uusitalo et al., 2005). Uncertainty in ES models can have a broad range of causes, ranging from uncertain input data, uncertain relations among the biophysical structure of ecosystems and ES delivery and uncertainties related to human preferences for ES (Hou et al., 2013). The absence of modelling approaches to deal with uncertainties and the absence of information on uncertainties are two important reasons that explain why uncertainties are often ignored in ES models. Another reason, specific for GIS-based models, is that it is time-consuming and complex, especially if spatial dependencies need to be taken into account, to propagate uncertainties. Only in case a limited set of parameters or datasets are responsible for the majority of uncertainties in the analysis, Monte Carlo simulations can offer a solution by propagating this uncertainty to the model output. In practice, however, this is rarely done in ES modelling studies (Seppelt et al., 2011).

1.4 Bayesian belief network models

The recent introduction of Bayesian belief network (BBN) models in ES assessment has the potential to overcome some of the aforementioned challenges because of their ability to deal with uncertainties and to integrate different knowledge types ranging from expert knowledge to empirical data. This flexibility towards input data enables the inclusion of a broader set of services as both well-studied and poorly-studied services can be included. Since their introduction by Pearl (1986), BBNs have been used in various scientific domains, in particular scientific problems related to uncertainties and human reasoning. In the past, BBNs have been frequently applied for medical diagnosis problems, classification problems and machine learning. Recent applications in the environmental modelling domain include habitat suitability models, risk assessments, management evaluation, decision support and, more recently, ES modelling (Aguilera et al., 2011). Compared to the broad categories of ES models discussed previously, BBNs are situated in between the GIS models, the data-driven look-up tables and the statistical models. Although the complexity of BBNs is generally lower than that of a GIS model, it is higher than that of data-driven look-up tables as they also attempt to model the system more or less mechanistically. Compared to statistical models, BBNs are more flexible regarding the data types they can handle. Spatial extrapolation of model results is comparable, but more complex than spatial extrapolation of data-driven look-up tables.

1.4.1 Theoretial background

BBNs are essentially non-parametric, statistical models that conceptualise the system being modelled as a network of nodes connected through arrows. In this network, nodes represent system variables, while arrows represent causal relations among these system variables. All variables in a BBN are discrete variables or discretised continuous variables. The levels or classes of these variables are referred to as states and are displayed in the network's nodes. Next to this qualitative component, BBNs also have a quantitative component that consists predominantly out of probabilities. Probabilities are used to define the probability of a variable being in one of its states and to quantify the strength of the causal relations in the model. The latter are referred to as conditional probabilities. Both the conditional probabilities and the network structure define the joint probability distribution over all the variables included in the model. It is this joint probability distribution that enables BBNs to calculate the probability of all kind of events as an answer on particular what-if questions. To increase the legibility of this section and following chapters, Table 1.3 provides an overview of BBN jargon used throughout this book.

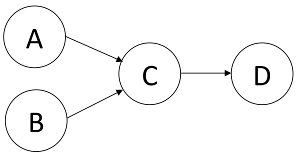
The network of a BBN model has some typical characteristics. First of all, the links between the nodes of a BBN model are all directed and can, thus, be represented by arrows. The nodes at both ends of an arrow are referred to as parent nodes (at the start of an arrow) and child nodes (at the end of an arrow). The direction of these arrows may either follow causal reasoning (link directed from cause to effect) or diagnostic reasoning (link directed from effect to cause). Arrows directed according to causal reasoning are generally preferred as they are easier to grasp and the complexity of the network will generally be lower (lower amount of links) in case only causal links are being used (Russell and Norvig, 2010). Another important feature of the network of a BBN is that it does not contain feedback loops or cycles. Because of these two characteristics, the network of a BBN model is called a directed acyclic graph or DAG. Aside from visually representing causal relations among the system's variables, the network also indirectly depicts independencies among variables in the model. Note that the absence of a causal link between two variables not necessarily implies that both variables are independent. The DAG in Figure 1.4 illustrates this complexity. According to the defined causal relations in this graph, variables A and B are independent (P(A,B) = P(A)*P(B) or P(B|A) = P(B)). However, A and B are not independent in case the status of variable C is known (P(A,B|C) $\neq$ P(A|C)*P(B|C)). On top, although no direct links are present, variables A and D are not independent. More information on how to identify these dependencies and independencies based on a DAG can be found in the work of Jensen and Nielsen (2007). Independencies, defined by the graph, are useful to calculate the joint probability distribution over the system's variables as they significantly simplify the chain rule of probability theory, the conventionally used equation to calculate the joint probability distribution over multiple variables (Equation 1.1).

$$P(A,B,C,D) = P(A) * P(B|A) * P(C|A,B) * P(D|A,B,C) \qquad (1.1)$$

Figure 1.4 illustrates how defining a causal network for four variables simplifies the calculation of the joint probability distribution over these four variables. The more links included in a BBN, the less independencies and the more complex the calculation of the joint probability distribution. For fully connected networks (maximum number of links without introducing feedback loops) the general chain rule

Table 1.3: An overview Bayesian belief network jargon.

Terminology	**Description**
directed acyclic graph or DAG	A network, containing nodes and arrows, that graphically represents a Bayesian belief network model.
node	Graphical representation of a variable in a Bayesian belief network model.
arrow	Graphical representation of a causal relation in a Bayesian belief network model.
parent and child node	Relative classification of nodes. Arrows originate in parent nodes and end up in child nodes.
state	Each variable in a BBN model has a set of states it can manifest. These states can be numerical values, discrete classes or qualitative levels.
directed edge or arrow	Graphical representation of a causal relation among two variables. Arrows are generally directed from the cause to the effect.
Probability distribution	If the state of variable A is uncertain, a probability distribution P(A) quantifies the probability of a variable being in one of its states. These probability distributions are represented by bar plots in each node of the network.
conditional probability	If the probability distribution of a variable A depends on the state of another variable B, this dependence can be encoded as a conditional probability P(A|B). These conditional probabilities quantify the causal relations that are represented by arrows.
conditional probability table or CPT	Tables that store the conditional probability distributions that quantify the causal relations in the network.
marginal probability distribution	The probability distribution of a single variable P(A), represented as bar plots in the model's nodes.
joint probability distribution	The probability distribution of two or more variables P(A,B) that quantifies the probability of two or more variables being in a particular state simultaneously.
evidence	Probabilistic (soft evidence) or deterministic (hard evidence) information on the state of a particular variable in the network.
instantiation	The process of inserting hard evidence into the network. Or, in other words, assigning a 100% probability to one of the states of a variable.
belief updating	If evidence is inserted into the network it will change the marginal probability of other variables in the network. This process is generally referred to as belief updating.
prior probability	The probability distribution of a variable before belief updating.
posterior probability	The probability distribution of a variable after belief updating.



$P(A, B, C, D)$

Chain rule of probability theory:

$= P(A) * P(B|A) * P(C|A, B) * P(D|A, B, C)$

Accounting for independencies encoded in the graph:

$= P(A) * P(B) * P(C|A, B) * P(D|C)$

General expression for BBNs:

$= \prod P(X|parents(X))$

Figure 1.4: Left: a directed acyclic graph denoting the causal relations among the variables A,B,C and D. Right: the independencies encoded by the graph simplify the calculation of the joint probability distribution considerably. Thus, Bayesian belief networks can be seen as tools to represent and calculate joint probability distributions more efficiently.

of probability theory will not be simplified. In other words, BBNs offer a way to more efficiently represent a joint probability distribution and to lower the calculation effort.

Figure 1.4 also shows which probabilities we need to quantify so that the model is able to calculate the joint probability distribution or, in other words, to make the model operational. For the input nodes A and B the marginal probability distributions P(A) and P(B) need to be known, while for the variables C and D the conditional probabilities P(C|A,B) and P(D|C) need to be defined. In a BBN, these probabilities will be stored in a conditional probability table or CPT, tables that are associated to each node in the network. Classically, these probabilities are derived from data or quantified based on available knowledge. After fully parameterising the model the marginal probability distributions P(A), P(B), P(C) and P(D) will be visualised as bar plots in the BBN model's nodes. These probabilities are all referred to as prior probability distributions. In case new information (evidence) on the status of one of the system's variables becomes available, the model will update these prior probability distributions (P(X)) to posterior probability distributions (P(X|evidence)), a process which is called belief updating. This evidence may be deterministic (100% sure about the status of a variable) or probabilistic (e.g. the state of the variable is either state a or state b, not state c). More information on the theoretical background of BBN models can be found in Jensen and Nielsen (2007).

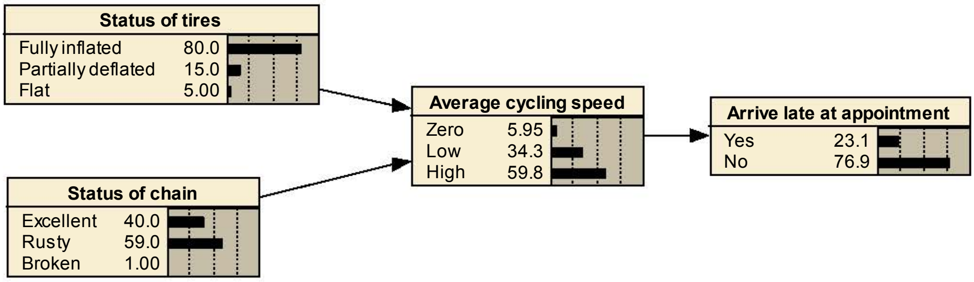


Figure 1.5: An example Bayesian belief network model to predict the time of arrival or to analyse the causes of arriving late while commuting by bike.

1.4.2 Illustrative example

To illustrate the functioning of a BBN, a simple model to predict arrival time when going to an appointment by bike is represented in Figure 1.5. The soundness of the causal network, presented in Figure 1.5, can be verified by logical reasoning. Intuitively, we know that average cycling speed will depend both on the status of the bicycle's chain and the status of the bicycle's tires. On top, one may assume that the status of the tires does not have an effect on the status of the chain or the other way around (note that in reality bad bicycle maintenance, as an external driver, may introduce a dependency between both events). Average cycling speed will have a direct effect on whether you will be late at your appointment. Although the time of departure also plays a crucial role to predict whether you will be late, this variable was not included in the network. This simplification, however, can be taken into account by introducing extra uncertainty while defining the conditional probability P(arrive late at appointment|average cycling speed). As an illustration, the CPT for the average cycling speed node is presented in Table 1.4. Aside from defining conditional probabilities, we also need to define the marginal probabilities P(Status of tires) and P(Status of chain) to make the model fully operational. For example, as we know that a broken chain rarely occurs when you take your bike out of the garage, we can assign a very low prior probability to this event (1%).

Once made operational, a BBN can be applied for different purposes. The model can be used to predict the status of the output variable given information on the status of the input variables or, the other way around, to predict possible causes (input variables) given information on the effect (output variable). The first, conventional way to apply a model is referred to as causal inference in the context of BBNs. The second way is referred to as diagnostic inference and is generally used to analyse a

Table 1.4: Conditional probability table for the average cycling speed (ACS) node in Figure 1.5.

Status of tires	Status of chain	P(ACS=Zero)	P(ACS=Low)	P(ACS=High)
Fully inflated	Excellent	0	0	100
Fully inflated	Rusty	0	50	50
Fully inflated	Broken	100	0	0
Partially inflated	Excellent	0	60	40
Partially inflated	Rusty	0	80	20
Partially inflated	Broken	100	0	0
Flat	Excellent	100	0	0
Flat	Rusty	100	0	0
Flat	Broken	100	0	0

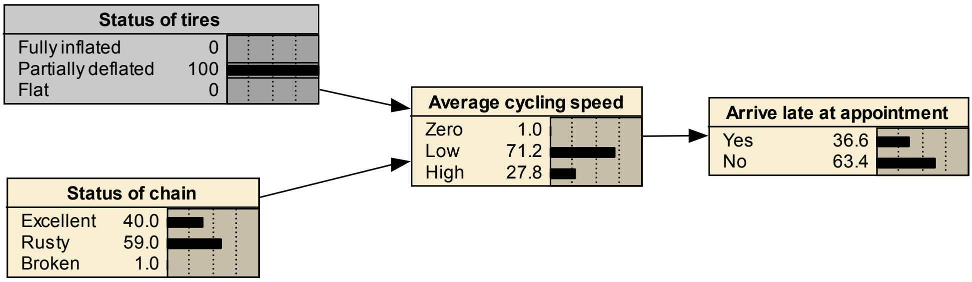


Figure 1.6: Causal inference with Bayesian belief networks.

system rather than to make predictions.

By applying the example model, presented in Figure 1.5, for causal inference we can infer, for example, the probability of arriving late given that we know that our tires are partially deflated. After belief updating, the chance for arriving late will change from 23.1% to 36.6% (Figure 1.6). Similarly, by applying the model for diagnostic inference, we can infer, for example, the probability of a flat tire being the cause of arriving late. After belief updating, the probability of having a flat tire will change from 5% to 21.7% (Figure 1.7).

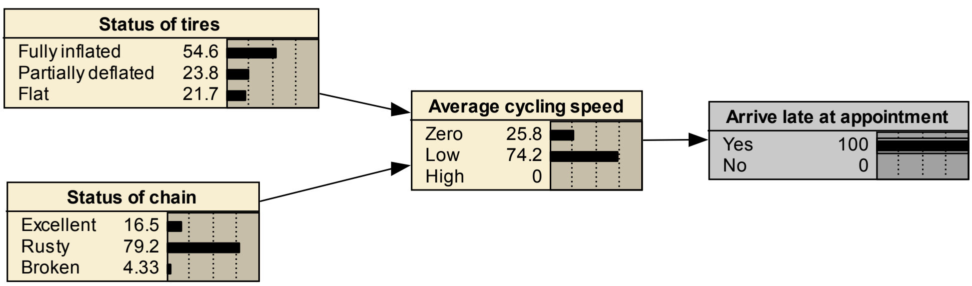


Figure 1.7: Diagnostic inference with Bayesian belief networks.

Similarly these models can be applied for reasoning related to the delivery of ES. Similarly to the presented example, ES delivery will depend on input factors, such as, land use and soil type and intermediate factors, such as, the suitability of the soil for a particular land use.

1.4.3 Dealing with uncertainty in Bayesian belief networks

As demonstrated by the example above, several types of uncertainty can be accounted for in a BBN model. These uncertainties can represent epistemic uncertainty, i.e. the uncertainty resulting from imperfect knowledge, or stochastic uncertainty, i.e. the uncertainty resulting from natural variability (Refsgaard et al., 2007; Walker et al., 2003). Data gathering will reduce epistemic uncertainty and will reveal stochastic uncertainty. The same happens in a BBN when new evidence is inserted in the model and beliefs are updated, lowering the share of epistemic uncertainty in the model output (see Figure 1.6). Besides knowledge on the nature of uncertainty, it is also important to know which sources of uncertainty are reflected in the model output. The sources of uncertainty considered in the models presented in this thesis include predominantly input uncertainty and parameter uncertainty. BBN models can, for example, provide estimates of ES delivery in case soil type is unknown or uncertain, an example of accounting for input uncertainty. Accounting for parameter value uncertainty is a good strategy to cope with the uncertainty associated to generalisation of natural systems (Hou et al., 2013). Instead of working with a single parameter value for the efficiency of forests to capture fine particulate matter, BBNs can work with probability distributions over several possible parameter values, representing the capture efficiency of different forest types. Nevertheless, the uncertainties that are accounted for in a BBN model and that are reflected in the model output are only a subset of the actual uncertainties we have to deal with. Sources of uncertainty, mentioned by Refsgaard et al. (2007), that are not reflected in the model output include model structure uncertainty, model context uncertainty and model technical uncertainty. Also not all types of model input uncertainty, such as uncertainty related to the quality of maps (see, for example, the work of Hou et al. (2013)), were considered in the models presented in this thesis.

1.5 General aim and research questions

Although BBNs are an established modelling technique in research domains, such as, medical diagnosis modelling and machine learning, they were only introduced in environmental modelling in the late nineties (Aguilera et al., 2011). From then onwards several ES-related BBN papers have been published. However, Haines-Young (2011) was the first who explicitly mentioned the ES concept in a BBN paper. The main motivations for this introduction were the modelling technique's ability to account for uncertainties and its ability to integrate different knowledge types in one integrated model. However, there is a huge step between acknowledging the usefulness of these features for the ES modelling research domain and implementing the technique to assess whether BBNs can really contribute to tackling the challenges mentioned in section 1.4. This study aims to pave the way for implementing BBNs for ES assessments and, by doing so, attempts to provide an answer to the following research questions:

1. The state-of-the-art of Bayesian belief networks in ecosystem service modelling
    (a) How are BBNs currently used in the ES research domain?
    (b) Are best modelling practices available?
    (c) What elements are missing to be able to use BBNs at their full potential?

2. Bayesian belief networks for local decision support
    (a) How can BBNs be applied to guide local management decisions?
    (b) Does accounting for uncertainties has an added value for decision support?
    (c) Are there risks associated to the use of BBNs in ES modelling?

3. Bayesian belief networks for regional ecosystem service assessment
    (a) How can BBNs be operationalised for regional ES assessments?
    (b) Can BBNs contribute to understanding interactions among services?
    (c) Can major drivers that determine ES delivery be determined using BBNs?

4. Bayesian belief networks for mapping ecosystem service delivery an associated uncertainties
    (a) How can BBNs be applied for spatially explicit ES assessments?
    (b) How can uncertainties be visualised on maps to support decision making?

5. Bayesian belief networks for analysing impacts of socio-economic developments
    (a) What is the impact of socio-economic development on ES in Flanders?
    (b) What is the added value of accounting for uncertainties in this scenario analysis?

1.6 A roadmap to the dissertation

Throughout this dissertation the use of BBNs to model ES delivery is systematically explored. The state-of-the-art of the use of BBNs can be consulted in chapter 2. In the following two chapters, the potentials of BBNs are being assessed, both in a small scale case study and at the regional level. Chapter 5 introduces a software framework operationalising BBNs to provide spatial information on ES delivery and associated uncertainties. Finally, the added value of BBNs for scenario analyses is investigated in chapter 6. In addition to this brief overview, the different chapters are shortly explained in the subsequent paragraphs.

In the introduction several challenges that the ES modelling community are currently facing have been discussed. These challenges include the need to bridge gaps among scientific disciplines ranging from ecology to socio-economy, dealing with limited available (spatial) data and omnipresence of uncertainties. After discussing the limitations of current models, BBNs have been proposed as an alternative modelling technique that has the potential to overcome some of these challenges.

Chapter 2 evaluates, based on a literature review, the strengths, weaknesses, opportunities and threats related to the use of BBNs in ES research. This chapter provides an answer to questions, such as, what are the strengths and weaknesses of the modelling approach, what kind of services are predominantly modelled and how are BBNs generally structured in ES research.

Chapter 3 evaluates the use of BBNs to assess ES delivery of a local freshwater pond, and highlights the opportunities and risks associated to the use of BBNs as decision support tool. The strengths, weaknesses and opportunities of the modelling approach, as discussed in the previous chapter, are evaluated with a focus on the use of BBN models as decision support tool.

Chapter 4 discusses the development of BBNs to model the delivery of ES in Flanders. This chapter focusses on the capability of BBNs to model a selection of ES based on different kinds of data sources ranging from expert knowledge to empirical data (monitoring data and survey data) . Through exploration of the developed models, the main drivers of ES delivery in Flanders are determined and interactions, such as, synergies and trade-offs among services are investigated.

Chapter 5 zooms in how ES delivery can be mapped based on BBNs. The chapter describes the development of an open-source GIS plug-in to bridge the gap between BBN and spatial analysis software and proposes several visualisation approaches to map BBN output and evaluates them regarding their decision support capacity.

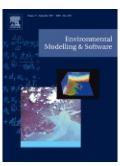
Chapter 6 discusses the influence of temporal dynamics on ES delivery with a focus on the interplay of land use change and ES. Model coupling between a cellular automata model to predict land use change and BBN models to predict ES delivery is discussed. By applying the coupled models, socio-economic impacts on ES delivery are analysed. On top, the importance of accounting for uncertainties is assessed.

The general discussion, main conclusions and opportunities for further research are provided in the final chapter of this dissertation.

2 A review of Bayesian belief networks in ecosystem service modelling

As discussed in the previous chapter, Bayesian belief networks have been recently introduced in the ecosystem services modelling domain. This chapter will review the use of Bayesian belief networks in ecosystem service modelling studies published since 2000 and will end with a SWOT analysis and some practical suggestions for using Bayesian belief networks to model ecosystem services. The SWOT analysis highlights the advantages and disadvantages of Bayesian belief networks in ecosystem service modelling and pinpoints remaining challenges for future research. The chapter concludes that Bayesian belief network models are suited to describe, analyse, predict and value ecosystem services. Nevertheless, some weaknesses have to be considered, including poor flexibility of frequently applied software packages, difficulties in eliciting expert knowledge and the inability to model feedback loops. The main opportunities for the use of Bayesian belief networks include modelling the full ecosystem services cascade and integrated modelling of well-studied and poorly-studied services.

This chapter is based on:



Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environmental Modelling & Software 46, 1-11.

2.1 Literature review

Table 2.1 gives an overview of recent BBN applications in the scientific literature on ES research. A Web of Science title search, using the keyword 'Bayesian network*', was performed to find all BBN-related papers within the 'environmental sciences and ecology' research domain (October, 2012). Only papers published from 2000 to 2012 were considered. As the ES term was often not explicitly mentioned, the selected articles were screened to determine whether or not they dealt with ES modelling. Case studies on ecosystem functions and services providing sufficient information on the model development process were selected. Furthermore, the reference lists of the selected articles were screened on papers relevant to the scope of this review. This resulted in a set of 47 publications (Table 2.1).

Several characteristics of the model development process are reviewed. BBN-related characteristics are the data sources used to develop the network or DAG and to populate the model's CPTs, the number of nodes used in the model, the applied software package and whether or not they included decision and utility nodes, respectively referring to input nodes that contain management decisions as states and nodes that evaluate the utility of these management decisions based on the output nodes of the model. ES-related characteristics include ES type(s), number of modelled ES, scale size or spatial extent, way of model validation, whether results are mapped and whether ES are valued in monetary terms.

Two-thirds of the applications listed in Table 1 are related to aquatic ecosystems and cover only a limited set of services (water regulation, genetic resources, recreation, water supply and food provision). A wide range of ES mentioned in the CICES-BE classification (Turkelboom et al., 2014), such as erosion prevention and air quality regulation are not covered. Sufficient process knowledge to develop mechanistic models to quantify ES like improved air quality, carbon sequestration in soils and erosion prevention is one possible reason for the lack of BBN applications (Skjemstad et al., 2004; Byun and Schere, 2006; Merritt et al., 2003). Scientifically, BBN models offer little added value to assess these well-documented ES. However, in a holistic ES approach, both poorly and well-documented services need to be considered. BBNs have the potential to provide the integrated framework for jointly assessing poorly documented ES with well-documented ones. However, only one third of the reviewed models do so (Table 2.1).

Table 2.1: List of scientific applications of Bayesian belief network models in ecosystem service modelling, published between 2000 and 2012. (S = stakeholder knowledge, E = expert knowledge, M = model simulations, D = empirical data; BDN = Bayesian Decision Network).

Author	**Ecosystem Services**	**Knowledge source**		**Number of nodes**	**Extent**	**Software**	**Decision support**			**Model validation**
		DAG	**CPT**				**map**	**value**	**BDN**	
Adriaenssens et al. (2004b)	genetic resources	E	D	6	/	Matlab				data driven
Ames et al. (2005)	water regulation; recreation	/	D, M	12	medium	Netica		x	x	sensitivity analysis
Barton et al. (2008)	recreation; water regulation	E	D, E, M	34	medium	Hugin		x	x	expert evaluation
Borsuk et al. (2006)	genetic resources	E	E	38	medium	Analytica				data driven
Borsuk et al. (2004)	genetic resources; recreation	E, S	E, M	14	small	Analytica				/
Bressan et al. (2009)	pest prevention	/	D	8	small	Genie	x			data driven
Bromley et al. (2005)	freshwater provision	S	D, M	66	medium	/				/
Chan et al. (2010)	freshwater provision	E, S	E	49	small	Netica				/
Chan et al. (2012)	genetic resources	E	D, E	24-27	large	Netica				data driven
Dlamini (2010)	wildfire prevention	E	D	13	large	Netica	x			data driven; sensitivity analysis
Dorner et al. (2007)	water regulation; food provision	E, M	E, M	12	small	Netica, Hugin	x	x	x	/
Farmani et al. (2009)	water regulation; food provision	S	D, E, M	22	small	Hugin		x	x	expert evaluation
Gawne et al. (2012)	food provision	E	E	44-52	large	Netica				data driven
Haines-Young (2011)	climate regulation	/	/	17	large	Netica	x			/
Hamilton et al. (2007)	pest prevention	E, S	D, E, M	23	small	Netica				/
Henriksen et al. (2007)	water regulation; food provision	S	D, E, M	24	small	Hugin		x	x	stakeholder evaluation
Howes et al. (2010)	genetic resources	E	D	8	medium	Netica				data driven
Hunter et al. (2009)	freshwater provision; water regulation	/	/	/	large	/		x		/

Johnson et al. (2010)	pest prevention	E	D, E, M	23	small	Netica, Hugin				expert evaluation; sensitivity analysis
Kragt et al. (2011)	water regulation	E, S	D, E	29	medium	/		x	x	/
Lehmkuhl et al. (2001)	genetic resources; recreation	E	D, E, M	12	large	Netica	x			sensitivity analysis
Marcot et al. (2001)	genetic resources	E	E	5 to 15	small	Netica	x			expert evaluation
Martín de Santa Olalla et al. (2007)	freshwater provision	E, S	D, E, S	56	large	Hugin				expert/ stakeholder evaluation
Martinez-Santos et al. (2010)	freshwater provision	E, S	D, E, M	42	large	Hugin				stakeholder evaluation
McDowell et al. (2009)	water regulation	S	D, E, M	41	large	Netica				sensitivity analysis; expert evaluation
Molina et al. (2010)	freshwater provision; primary production	E, S	D, E, M	31	large	Hugin		x		based on existing models; stakeholder evaluation
Nash et al. (2010)	food provision; water regulation	E, S	D, E, M, S	31	small	Netica				sensitivity analysis; expert evaluation
Newton et al. (2006)	fibre provision	E	D, E, S	99	/	Hugin				stakeholder/expert evaluation
Newton et al. (2007)	genetic resources	E	D, E	2 to 11	/	Hugin			x	/
Park and Stenstrom (2006)	water regulation	/	D	10	small	C++	x			data driven
Pellikka et al. (2005)	genetic resources; recreation	E	E	18	large	FC BeNe		x		expert evaluation
Pérez-Miñana et al. (2012)	climate regulation	E,M	E, M	15 to 20	large	Agena-Risk				based on existing models
Pollino et al. (2007a)	genetic resources	E,S	D, E	45	medium	Netica				data driven
Pollino et al. (2007b)	genetic resources; water regulation	E	D, E	35	medium	Netica				data driven; sensitivity analysis

Pullar and Phan (2007)	genetic resources	E	D, E	7	medium	Netica	x			sensitivity analysis
Raphael et al. (2001)	genetic resources	E	D, E	15	large	Netica	x			/
Rieman et al. (2001)	genetic resources	E	E	24	large	/	x			sensitivity analysis
Shenton et al. (2010)	genetic resources	E	D, E, M	20	medium	Netica				sensitivity analysis; data driven
Shihab (2008)	water regulation	E	D	12	medium	Hugin				/
Smith et al. (2007)	genetic resources	E	E	12	large	Netica	x			data driven
Steventon and Daust (2009)	genetic resources	E	D, E, M	17	large	Netica				sensitivity analysis
Tattari et al. (2003)	genetic resources; water regulation	E	E	25	small	FC BeNe				sensitivity analysis
Ticehurst et al. (2011)	genetic resources	E	S	13	large	Netica				sensitivity analysis; expert evaluation
Ticehurst et al. (2007)	genetic resources; cultural services; food provision; regulating services	E,S	D, E, M	37	medium	ICMS		x	x	data driven; expert evaluation
Wang et al. (2009)	freshwater provision; food provision	E	E	34	medium	Netica				expert/ stakeholder evaluation; data driven
Wooldridge and Done (2003)	genetic resources	E	E	6	large	Netica				data driven
Zorrilla et al. (2010)	freshwater provision	E, S	D, E, M	59	large	Hugin		x		stakeholder evaluation

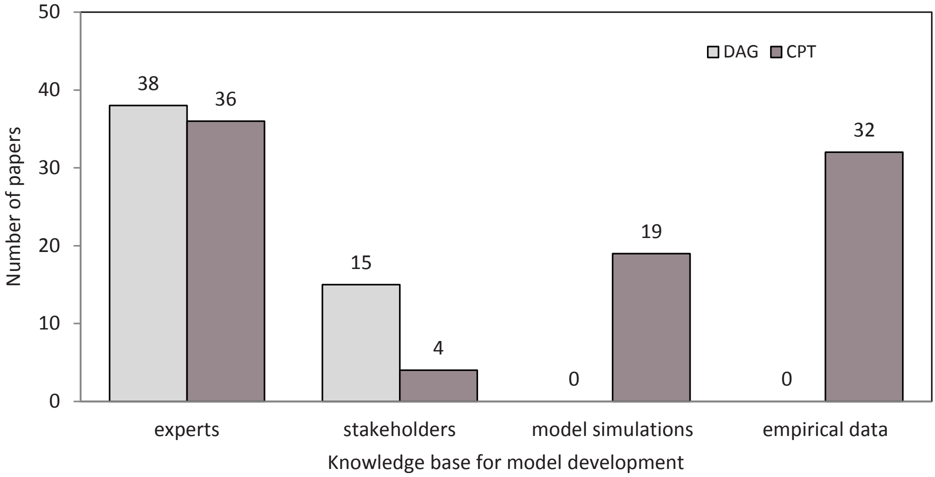


Figure 2.1: Use of expert knowledge, stakeholder knowledge, model simulations and empirical data in the model development processes of the reviewed studies.

The knowledge base for model development differs largely between the listed applications. Development of a BBN model consists of construction of the causal network and definition of the CPTs. The model development process can be based on directly implementable knowledge like relations derived from model simulations or expert and stakeholder knowledge. Throughout this chapter, scientific experts and land managers are referred to as experts, while local dwellers and public representatives are referred to as stakeholders. Indirectly implementable knowledge like empirical data is a second potential knowledge source. Through model learning, data can be converted into knowledge embedded in the model. Including expert and stakeholder knowledge in addition to data can accommodate both limited data availability and the necessity to include stakeholders when assessing the societal benefits obtained from ecosystems. Due to limited data availability, model development of 65% of reviewed models was based on a mixture of expert/stakeholder knowledge and empirical data. Usually, a common model development protocol is followed. First, experts and stakeholders are consulted to define the services related to the ecosystem and to develop a basic DAG structure. Second, experts and data are consulted to refine the model structure and to populate CPTs. This common model development protocol is clearly reflected in the distribution of used data sources, shown in Figure 2.1. If sufficient data are available as in primary production modelling at field scale, experts are merely consulted to define the model structure while the CPTs are populated based on empirical data only (Tari, 1996).

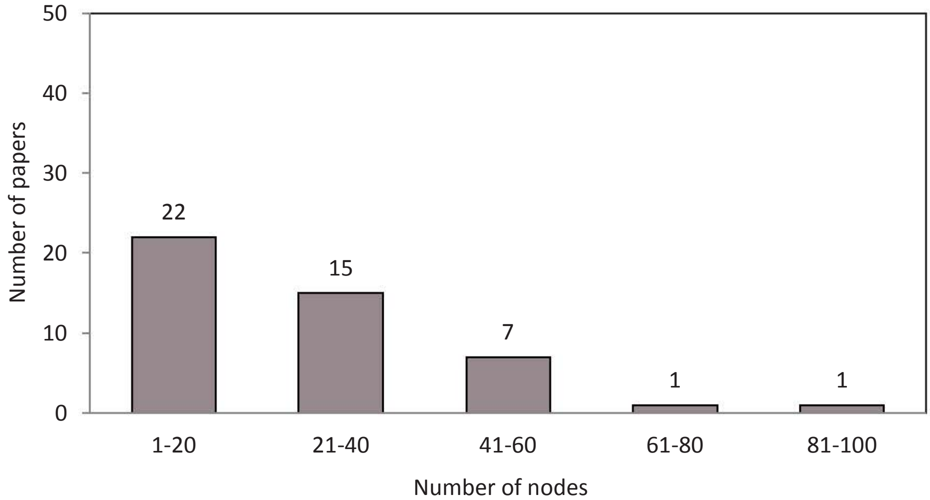


Figure 2.2: Variation in node numbers of the reviewed studies as a measure of model complexity.

The number of nodes, together with the amount of causal relations and the number of states per node, define the complexity of a BBN model. As stated by Marcot et al. (2006), high node numbers, often resulting in a lot of intermediary layers between the layer of input nodes and the layer of output nodes, can weaken the relation between input and output nodes. To prevent this dilution of interactions, it is recommended to limit the number of node layers or sequential relationships to less than five (Marcot et al., 2006). However, a low number of layers, generally associated with a relative low number of nodes, implies considerable simplification of the modelled system. In the reviewed applications the amount of nodes is kept relatively low, safeguarding the functionalities of the BBNs according to the aforementioned guidelines. 80% of the models have a node number lower than 40 (Figure 2.2).

The spatial scale of listed applications varies considerably. Studies with a small extent (<100 km^2), medium extent (100-1000 km^2) and a large extent (>1000 km^2) are more or less equally represented in Table 2.1.

Commonly used software packages are Netica (Norsys Software Corporation, 1998) and Hugin (Hugin Expert, 2008). 80% of the reviewed studies apply one or the other. Both packages provide an efficient Bayesian inference algorithm embedded in a comprehensible user-friendly interface equipped with a range of useful tools. However, compared to open source packages, they require a user license and are less flexible towards coupling with other software packages. For such packages, only Application Programming Interfaces (APIs) can do the trick. Software coupling has the potential to overcome some of the weaknesses related to BBNs. Coupling with GIS, for example, enables the inclusion of spatial interactions, which are otherwise difficult to implement in a BBN (Giretti et al., 2012). Moreover, software integration offers the potential to couple ES BBNs with established ES models. The use of programming languages such as C++ and custom-written Bayesian inference algorithms is another possibility to increase flexibility (Park and Stenstrom, 2006). Bressan et al. (2009) applied SMILE/GeNie (Druzdzel, 1999). This software package is freely available and features more flexibility towards coupling with GIS.

Modelling and representing ES spatially explicit has a lot of added value for decision makers. One-third of the reviewed literature combines modelling and spatial mapping of ES. The majority of the reviewed studies apply BBNs on entities (e.g. watersheds (Ticehurst et al., 2007), bays (Johnson et al., 2010)). Such models are generally referred to as spatially lumped models (Kelly (Letcher) et al., 2013). Although the link between GIS tools and BBN software is being explored in current research, it is often restricted to mapping of BBN outputs based on georeferenced inputs (Johnson and Mengersen, 2012; Stelzenmüller et al., 2010; Stassopoulou et al., 1998). GIS tools are predominantly employed to collect spatial input data that are used as BBN input on a polygon or pixel basis. However, no standardised, generally applicable frameworks are being proposed to carry out this coupling with GIS. The obtained probabilistic BBN outputs are mapped in a next step either by using the most probable state or by using the mean expected value (e.g. Dlamini, 2010; Smith et al., 2007). Incorporation of spatial dependencies in the DAG of BBNs, such as, neighbourhood dependencies, has been less frequently tested in current BBN research (Giretti et al., 2012).

As a tool to inform management decisions, Bayesian decision networks (BDNs) can be used in combination with ES valuation (Kragt et al., 2011). Among the applications listed in Table 1, only 15% apply BBNs as decision networks (e.g. Barton et al., 2008; Kragt et al., 2011; Ticehurst et al., 2007). As the name suggests, BDNs attempt to predict optimal management practices to support decision making. To do this, two special node types are included in the model: a node that contains management options as states, referred to as a decision node, and a node that evaluates the different management options, referred to as a utility node. The utility node accounts for both the cost of management options and the benefits generated through ES delivery, enabling cost-benefit analysis of alternative management options. Based

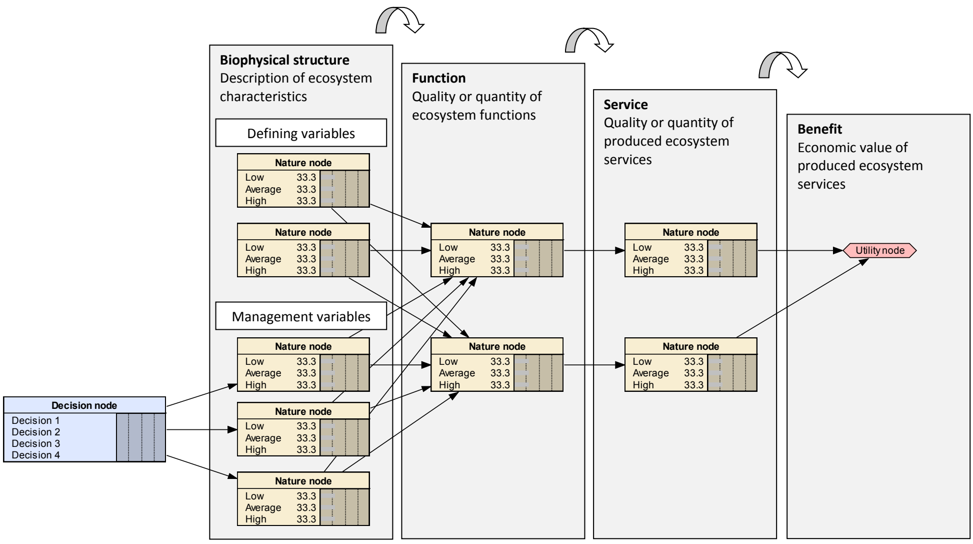


Figure 2.3: General layout of Bayesian decision networks for ecosystem service modelling, embedded in the 'ecosystem service cascade' (Haines-Young and Potschin, 2010). The term 'Defining variables' refers to input variables that are not amendable through management decisions.

on this utility node, a BDN automatically selects the optimal management option from the ones included in the decision node. Frequently used valuation techniques compatible with BBNs are contingent valuation and choice experiments, two types of surveys that can be used to infer people's willingness-to-pay (WTP) for changes in multiple environmental assets (see also the work of Hoyos (2010)). These WTP-functions, statistically derived from survey data, can easily be integrated into BBN utility nodes. Most valuation techniques in the reviewed studies are restricted to recreational use and have limited complexity levels (e.g. no spatial interactions) (e.g. Kragt et al., 2011; Ames et al., 2005; Gawne et al., 2012). Figure 2.3 shows the general layout of a BDN and illustrates the suitability of BBNs to model the entire chain of ES delivery. This chain of ES delivery, often referred to as the 'ES delivery cascade', is a graphical representation of the different key elements of discussion in ES modelling and is in fact a simplification of the production process of ES (Haines-Young and Potschin, 2010). The concept of consequential ES cascades corresponds largely with how BBNs are structured.

Only one-third of the reviewed cases use data for model validation. The limited availability of data in ES modelling stresses the importance of robust model validation tools that do not depend on data. Model validation in 50% of the reviewed cases is based on expert or stakeholder evaluation and sensitivity analysis. A sensitivity analysis calculates the degree of contribution of various system variables to the output variables. Generally, a sensitivity analysis is carried out to communicate final model behaviour to the experts involved. Experts can check if the contributions of these system variables match their expectations based on system understanding. In 25% of the reviewed papers, model validation is not discussed.

2.2 SWOT analysis

The potential of BBNs in ES modelling can be explored through a SWOT analysis. This strategic assessment allows identifying the Strengths, Weaknesses, Opportunities and Threats related to the use of BBN models in ES modelling. This provides a clear view of the current abilities and the future potentials of BBNs in ES modelling. The use of SWOT to assess methodological frameworks has been successfully demonstrated in the past (e.g. Vonk et al., 2007).

2.2.1 Strengths

A first strength highly relevant in ES research is the potential to use both expert knowledge and empirical data. This is an important advantage in cases of limited data availability (Aguilera et al., 2011; Haapasaari and Karjalainen, 2011; Wang et al., 2009; Cain et al., 2003). The reviewed case studies clearly demonstrate this strength. In cases where data were lacking, additional relationships could be added to the models by using expert knowledge (e.g. Chan et al., 2012). Other case studies used expert knowledge upon empirical data as in classic Bayesian data analysis to adjust or strengthen data driven relations, generally referred to as CPT updating (e.g. Pullar and Phan, 2007). Nevertheless, some difficulties related to expert knowledge elicitation can be noted. While experts are generally comfortable to inform the network design, getting experts to express the relationships between nodes in terms of probabilities is more difficult. Deducing probability distributions out of a limited number of expert opinions (Keith, 1996; Morgan and Henrion, 1992) is often hard, especially for larger models. Because experts are usually more confident with small models representing a limited amount of causal links within one scientific discipline, division of the model into submodels can tackle this problem partly (Armstrong et al., 1975).

The suitability of BBN models in a participatory modelling approach, which Fish (2011) denoted as an essential aspect of ES assessment, is a second strength (Castelletti and Soncini-Sessa, 2007). Transparent BBNs encourage participation in model development and enhance communication between modellers, ecological experts, economists, stakeholders and decision makers, with the network as a common language. (Henriksen et al., 2007; McCann et al., 2006; Cain et al., 2003; Bacon et al., 2002). This in turn leads to a better inclusion of numerous opinions, needs and concerns related to ES (Zorrilla et al., 2010; Borsuk et al., 2001; Cain et al., 1999). BBNs also support the use of linguistic data, often occurring in social research related to ES (Smith et al., 2011). The suitability of BBNs for participatory modelling has been illustrated in several applications of BBNs within the MERIT (Management of the Environment and Resources using Integrated Techniques) stakeholder involvement procedure for integrated water management (Zorrilla et al., 2010; Farmani et al., 2009; Bromley et al., 2005). Providing a clear and transparent picture on how ecosystems can contribute to human well-being is a key factor in ES research. This transparency and the ability to use BBNs as diagnostic tools can enhance system understanding (Milns et al., 2010; Castelletti and Soncini-Sessa, 2007). System understanding will be crucial towards the potential adoption of ES models by end-users (McIntosh et al., 2011).

BBNs are suitable to be used in an adaptive modelling framework (e.g. Lynam et al., 2010; Howes et al., 2010) because of the ability to update individual causal relations independently (Castelletti and Soncini-Sessa, 2007). Given the emerging scientific research on ES, new information becomes available regularly, which necessitates model updating (McCann et al., 2006). BBNs designed for decision support can also benefit from an adaptive modelling approach. Scenario outcomes can be used to update a model, resulting in better informed decisions (Lynam et al., 2010).

Another advantage of BBNs is their explicit treatment of uncertainties. Measurements, especially in natural environments, and natural processes are common ES model aspects that are inextricably linked with uncertainties. Although taking into account uncertainties is valuable, integration of uncertainties in decision support models in the past has frequently led to an increase in model complexity and a decrease in model applicability (McIntosh et al., 2011). BBNs can overcome this drawback through their ability to integrate and communicate uncertainties more clearly. BBNs include these uncertainties in their probabilistic rule set. Because of the causal link between input and output nodes, uncertainties are propagated to the output nodes and are subsequently communicated as probability distributions in these output nodes. Similar representations of uncertainty can be obtained with other modelling techniques such as Monte Carlo simulations. However, BBNs are generally more efficient. BBNs instantly calculate the whole probability distribution of model outputs given the probability distribution of model inputs, which favours them in terms of computational performance in the case of frequent model updating (Nash and Hannah, 2011; Uusitalo, 2007).

A final strength of BBNs is the availability of a variety of model validation tools. Although data-driven model validation is commonly accepted, it is less suitable in data-poor research as ES modelling. In addition to data-driven validation, BBNs offer a broad range of validation techniques such as expert-based validation and sensitivity analysis (e.g. Ordóñez Galán et al., 2009). In cases of limited data availability, visual evaluation of BBN graphs by experts and stakeholders is also possible due to their high transparency (Aguilera et al., 2011; Cain, 2001).

2.2.2 Weaknesses

An important weakness of BBNs to model ES is their limited capacity to model all mechanistic processes that are involved. As some natural processes, responsible for the production of ES, are well-documented, mechanistic models may be desirable to model them. The exclusive use of discrete variables and the absence of feedback loops are at the heart of this limitation. Absence of feedback loops is frequently mentioned as a critical restriction of BBNs (Castelletti and Soncini-Sessa, 2007; McCann et al., 2006; Nyberg et al., 2006). This is especially true when complex processes are modelled. Modelling ES implies modelling ecological processes, coupling supply and demand and modelling complex spatial interactions (McCann et al., 2006). This system complexity is generally difficult to grasp without feedback loops and this may limit the quantitative model performance of BBNs. The potential of BBNs to combine multiple submodels with acceptable complexity levels to a synoptic whole is an option to account for the inherent complexity of ES provisioning processes (e.g. Barton et al., 2008). Exclusive use of discrete variables is a second weakness of BBNs. Most BBN inference algorithms work with discrete variables. This explains the need to define multiple states for each variable during model development. This discretisation often causes information loss (Aguilera et al., 2010; Jensen and Nielsen, 2007). The use of numerous states in each node reduces information loss. However, this will lead to missing data for some intervals and bulky CPTs that reduce model performance given equal data availability (Uusitalo, 2007; Myllymaki et al., 2002).

Another weakness mentioned previously is the limited flexibility of the frequently used BBN software packages. Over fifty percent of the reviewed case studies apply the modelling shells Hugin (Hugin Expert, 2008) and Netica (Norsys Software Corporation, 1998). From the listed applications, only Park and Stenstrom (2006) use the C++ general purpose software language. C++ is less user-friendly but features increased flexibility towards coupling with existing models and decision support systems. Open source software packages combining transparency, user-friendliness and flexibility would be desirable.

2.2.3 Opportunities

Due to a growing interest in ES, the number of applications of BBNs in ES modelling is increasing. This may lead to improved model development protocols, implementation methods and knowledge exchange. Growing interest of statisticians and mathematicians in practical applications can offer additional opportunities for BBN application in ES modelling.

An important asset of BBN models is the possibility to separately model single ES production processes and to couple several submodels in one BBN (Haines-Young, 2011). Complex processes can be cut into pieces and modelled independently (Kelly (Letcher) et al., 2013). ES modelling approaches often start with defining the production chain of the services. This production chain is frequently represented by means of the 'ES delivery cascade' (Haines-Young and Potschin, 2010) (Figure 2.3). The major benefit of this representation is the possibility to consider all processes, each related to a single scientific discipline, separately. Therefore, the cascade can be used as basis for a multidisciplinary modelling framework. Biophysical ES delivery processes and ES valuation are two steps in the cascade that can be sequentially modelled using BBNs. In ES modelling, integration of multiple submodels in one BBN was carried out by Dorner et al. (2007); Marcot et al. (2001); Rieman et al. (2001).

Other opportunities related to the usage of BBNs in ES modelling include optimisation of inference algorithms and the use of advanced BBN structures offering additional functionalities. Recent advances in inference algorithms have led to hybrid BBN models that allow the use of continuous data (Shenoy and West, 2011; Aguilera et al., 2010; Moral et al., 2001; Castillo et al., 1997). The use of continuous variables, however, requires more complex mathematical models (Aguilera et al., 2011). Optimisation of these hybrid modelling techniques is an opportunity towards the future (Shenoy and West, 2011; Aguilera et al., 2010; Moral et al., 2001). Other advances in inference algorithms can result in increased calculation speed and enhanced computational capacity. Examples of recent advances in BBN structures are object oriented BBNs (OOBNs), dynamic BBNs (DBNs) and Bayesian decision networks (BDNs) (discussed in detail in section 2.1). OOBNs are useful when the modelled system can be divided into multiple separate objects with lower complexity levels. These objects can be modelled separately before merging them into an integrated model. This modelling approach is especially useful if different information sources, spatial scales and complexity levels are applied for each modelled object (Aguilera et al., 2011). As mentioned by Haines-Young (2011), modelling multiple subprocesses, related to different disciplines, and combining them in an integrated whole offers great potential in ES research. In the reviewed articles, OOBNs are applied by Molina et al. (2010); Johnson et al. (2010) and Barton et al. (2008). DBNs, also referred to as time-sliced models (Kjaerulff, 1995), are suitable when temporal feedbacks need to be taken into account and when the modelled system contains time dependent variables. In a DBN, a BBN is replicated for several time steps, sequentially chained and computed. Thus, output nodes and input nodes of networks that represent subsequent time steps are linked (Cain, 2001). Adding nodes which define the time frame of the model is another frequently applied approach to account for temporal dynamics (Bashari et al., 2008; Liedloff and Smith, 2010). Although a limited number of the reviewed literature makes use of DBNs, the opportunities are clearly demonstrated (Johnson et al., 2010; Nyberg et al., 2006; Tremblay et al., 2004).

Spatially explicit modelling of ES often involves the use of raw remote sensing data, raster and polygon maps and complex spatial operations. Developments in the domain of high performance computing can significantly reduce calculation time when BBNs are applied spatially (Lee et al., 2011). The emergence of continuous online data loggers that are able to transfer data to a central database and state-of-the-art sensors to measure fine resolution environmental data are also promising (Li et al., 2012). Together with current efforts to develop extensive national and international environmental databases, this progress will lead to a significant increase in data (Fernandez et al., 2011; Rezaei et al., 2011). An advantage for BBNs in this context is the possibility to easily update existing models with newly available data.

2.2.4 Threats

In ES modelling and valuation, empirical data is often unavailable. Limited measurability of ES quantities and their social-economic importance is a major reason for this lack of data (Kareiva et al., 2011). As mentioned before, data dependency

Table 2.2: SWOT-analysis of Bayesian belief network applications in ecosystem service modelling.

Strengths	Weaknesses	Opportunities	Threats
- potential inclusion of both expert knowledge and empirical data - suitability for participatory modelling - suitability for adaptive management - explicit treatment of uncertainties - broad range of validation tools apart from data-driven validation	- limited capacity to model complex systems due to the absence of feedback loops and data discretisation - current software packages offer limited software integration possibilities	- growing interests in ecosystem services and ecosystem service modelling - multidisciplinary cascade approach: coupling of various submodels - expansion of current knowledge on Bayesian belief networks and related inference algorithms - increasing availability of environmental data	- limited data availability - single disciplinary model development - limited public model acceptance - limited scientific model acceptance

of BBNs is reduced by the possibility to partly rely on expert knowledge (Uusitalo, 2007; Marcot et al., 2001).

Single disciplinary model development is a second important threat. BBNs can be easily developed based on the knowledge of a single expert or based on subjective assumptions of the modeller. McBride et al. (2012) showed that knowledge derived from a single expert can sometimes be inaccurate. Ideally, expert knowledge should be collected objectively by consulting multiple experts, within multiple research domains. Models solely based on expert knowledge may be perceived as subjective or 'unscientific', which may threaten the credibility of BBNs.

A more general threat related to all ES models is model credibility. Public and political acceptance of ES models is often low due to the necessary, but grave simplification of the modelled social and ecological systems (McCann et al., 2006; Noon and Murphy, 1994). Although better model understanding can enhance model acceptance, limited complexity of BBNs can also form a serious threat by decreasing model acceptance due to oversimplification of the modelled system. In addition to public and political acceptance, also scientific acceptance is crucial to establish BBN models in ES research. Currently, BBNs are not yet widely accepted among scientists (Nash and Hannah, 2011).

2.3 Model development guidelines

Based on the examined applications of BBNs in ES modelling, some valuable lessons concerning practical model development and model validation can be learned. In this section, the applied model development approaches are evaluated to suggest optimal model development and validation procedures. Selection of input and output variables, model development, model complexity and validation techniques are subsequently discussed.

2.3.1 Input variables

Input variables can be classified as (1) variables that set up the system bases - defining variables; and (2) variables that represent system disturbances - controlling or management variables. Typical input variables of the first type are soil characteristics and climate. They predominantly define the opportunity of an ecosystem to deliver ES and are not amendable through land management. They are however essential to include as they can vary spatially and thus determine the potential of ecosystems to deliver specific services on specific locations. The second type of variables are related to ecosystem disturbance or ecosystem management practices and allow assessing the effect of management practices on ES delivery which is of high importance in management or decision support. To avoid unnecessary complication of the model, only input variables that substantially influence the delivered ES have to be taken into account. Although omitting variables may lead to information loss and more uncertainties, these newly introduced uncertainties can be accounted for in the CPTs of the other nodes in the model.

Additional criteria for the selection of input variables are the possibility to predict or observe changes in the variables. Only for observable variables, data can be collected and used during model development and model validation. Using observable input variables will often increase the perceived reliability of the models (Pollino et al., 2007a; Borsuk et al., 2004). In case certain variables are not measurable, BBNs have the potential to transparently include proxies for these variables. The relations between the easily measurable proxies and the real input variables of the model can be probabilistically quantified based on expert knowledge. This is a transparent expression of the confidence of the modeller in the used proxies (Murray et al., 2012; Smith et al., 2007, 2012). Considering the spatial heterogeneity of ES delivery, input variables are preferably spatially referenced. Moreover, spatial-explicitness facilitates the application of BBN models at either pixel or region level.

2.3.2 Model development

The preferred ES BBN model development protocol includes the use of multiple knowledge sources. As a first step in model development, experts and/or stakeholders can be consulted during DAG development. Data-driven DAG development is less desirable in ES modelling as it will only result in reasonable outputs when data are extensively available. As a second step in model development, CPTs can be quantified based on data, expert knowledge and/or stakeholder knowledge. The potential integration of expert knowledge in each model development step increases the flexibility of the model towards the integration of relations that are not supported by data. Alameddine et al. (2011) mentioned this as an important strength of BBNs. However, expert knowledge should be used with care. Abundant use of expert knowledge (either established or not) in CPT definition may be perceived as subjective or 'unscientific' and can reduce model acceptance by scientist and/or policy makers. Busch et al. (2012) recognised this as an important challenge related to all qualitative, expert-based modelling approaches. Possibilities to tackle this challenge include gathering multiple experts as knowledge source, validating expert knowledge with literature and including independent experts during the validation stage.

2.3.3 Model complexity

Two factors are regarded as most critical to successfully respond to the societal demand for ES models, namely model understanding (Fish, 2011) and model reliability (Kareiva et al., 2011). Both factors are closely linked to model complexity. Excessive model complexity will decrease model understanding, which in turn may decrease model acceptance and may impede participation in model development and evaluation. Moreover, complex models will prolong calculation time, will often hamper model adoption in practice, and are more data-hungry (Borsuk et al., 2004). Simple models, on the other hand, can decrease model reliability, which in turn can decrease model application in decision support systems and management evaluation tools. Therefore, the complexity level of ES models should be well balanced. While the graphical representation of most BBN models is relatively simple compared to other modelling techniques, the use of numerous links and variables can considerably increase the complexity of ES BBNs (Ordóñez Galán et al., 2009; Getoor et al., 2004; Cain, 2001; Jensen and Nielsen, 2007). Complex ES models require more data to achieve acceptable model performance (Aguilera et al., 2011; Tremblay et al., 2004). As with any modelling study, care should be taken to avoid excessive model complexity, and to tailor the BBN to specific research questions under investigation.

Model aspects influencing model complexity are the number of nodes and node layers, the number of states per node and the number of relations between nodes. A crucial step during model development to significantly reduce the model complexity is the selection of the set of states for each network node. The number of states per node affects model complexity through the size of the CPTs. Using a broad set of states will generally reduce information loss due to discretisation, however, it will considerably increase the size of the CPTs and the amount of necessary data or expert knowledge to populate the CPTs. To reduce complexity during model development, the set of states per node can be reduced or grouped to the most significant ones.

2.3.4 Output variables

Most of reviewed studies focus on only one ES (e.g. Dlamini, 2010; Johnson et al., 2010; Smith et al., 2007). However, simultaneous modelling of diverse ES would enable trade-off and synergy analysis, and assessment of multi-purpose measures (Ticehurst et al., 2007). Coupling of individual ES BBNs offers the opportunity to expand existing BBNs towards models that assess bundles of ES. Nevertheless, only one third of the reviewed case studies assess more than one ES. To reduce model complexity when assessing multiple output variables, it is important that only ES relevant within the scope of the research are selected. Typically, the relevance of an output variable will be high if the benefits derived from the ES are high, if provision of the ES is amendable by management or policy decisions, and if the ES can be appropriately represented at the spatial scale of the model. When comparing multiple ES, attention needs to be given to the unit in which the different ES are expressed. Monetary values provide one way of ensuring comparability of ES production rates. Further network expansions with nodes describing monetary values of delivered ES are demonstrated, for example, by Kragt et al. (2011). 80% of the reviewed BBNs do not include monetary value nodes.

2.3.5 Model validation

As mentioned before, validation of ES models is complicated due to the limited availability of empirical data for model outputs. Validation data is often missing when outputs are expressed as economic or social values or when the effects of future scenarios are evaluated (Kareiva et al., 2011; Farmani et al., 2009). Often, data can be obtained to validate several submodels of a BBN. For these submodels data-driven validation methods, splitting up the available data in a training set and a test set, can be applied (e.g. Howes et al., 2010). Sensitivity analysis and expert evaluation of the graphical structure are additional potential evaluation tools (Aguilera et al., 2011). Model evaluation by experts can be done both by discussing the relevance of model outputs generated for different test scenarios or by expert evaluation of the model structure itself. The latter is more difficult. Because of high model transparency of BBNs, stakeholder consultation during model evaluation is also possible.

2.4 Discussion

The reviewed literature indicates that BBNs have high potential in ES modelling. However, the use of BBNs is not always justified. According to Castelletti and Soncini-Sessa (2007), BBNs should be preferably used when knowledge is unstructured or merely based on empirical relations. For some well-documented ES, the previous assumption does not hold. For example, as a lot of process-based models are already developed to model carbon sequestration, the added value of a BBN for this individual ES may be very low. On the other hand, as part of more integrated ES models, a BBN of carbon sequestration can still be very useful. Integrated BBN models, modelling different ES, have an important added value because they are able to predict simultaneously the delivery of multiple ES and their trade-offs, they allow involvement of both stakeholders and experts and they allow modelling the uncertainties involved. To accomplish this goal, multidisciplinary knowledge has to be structured and merged.

As discussed in the previous chapter, numerous modelling techniques are already being applied to model ES delivery. The current leading ES modelling and mapping tool is InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) (Kareiva et al., 2011). BBNs can be used in parallel with the available tools as they offer different functionalities. The aim of BBNs is generally more focussed on conceptual modelling of ES, and on providing additional insights as a more integrative approach (Haines-Young, 2011; Liedloff and Smith, 2010). Compared to the in the previous chapter discussed modelling techniques to model ES delivery, BBNs can be considered as models with an intermediate complexity level that can make use of both empirical data and expert knowledge. These features locate BBNs in the middle of the graph represented in Figure 1.2. Another popular modelling technique with an intermediate complexity level that is able to make use of both empirical data and expert knowledge and that can deal with uncertainties is fuzzy logic. The suitability of fuzzy logic models to integrate expert knowledge is comparable with BBNs and hence entails similar practical difficulties as observed in BBNs (Adriaenssens et al., 2004a). A major advantage of fuzzy logic models is that they are based on possibility theory rather than probability theory and, thus, can deal with imprecision of knowledge. Although it is essentially a philosophical discussion on the meaning of probability, some argue that human knowledge is inextricably linked with imprecision and, therefore, not rich enough to be dealt with by probability theory as done in a BBN (Dubois, 2006). On the other hand, graphical model representation and the availability of more elaborated system exploration tools are important advantages of BBNs over fuzzy logic. Promising techniques that have been recently introduced to deal with imprecise knowledge in graphical models include credal networks (Cozman, 2000) and possibilistic graphical models (Ayachi et al., 2014). However, inference algorithms for possibilistic graphical models are less advanced compared to Bayesian inference algorithms (Borgelt et al., 2000).

2.5 Conclusion and recommendations

Current ES research focusses mainly on complex mechanistic models while conceptual modelling techniques like BBNs remain underutilised. This literature review clearly illustrates the potentials of BBNs in the ES research domain. While applications of participatory processes to develop and evaluate BBN models rapidly evolve and are becoming more and more advanced, several limitations of the modelling techniques traditionally end up in the shortcomings section of most published studies. The existing missing link between BBN and GIS software and the existing prejudice that BBNs are subjective models are examples of such limitations that may hamper the operationalisation of BBNs in the ES research domain. Furthermore, the potential of BBNs remains underutilised. While BBNs offer an ideal framework to integrate the delivery processes of multiple ES in one integrated model, only a minority of the reviewed studies considered multiple services, and none of them investigated ways to apply BBNs for analysing interactions among services.

The following chapters focus on ways to overcome some of these remaining challenges and to fully explore the potentials of the modelling technique. While chapter 3 and 4 investigate the use of BBNs to model the full cascade of ES delivery for local and regional ES assessment, respectively, chapter 5 proposes a way to bridge the existing gap between BBN and GIS software.

3 A local application of Bayesian belief networks for ecosystem service modelling

The previous chapter discussed the state-of-the-art of the use of Bayesian belief networks in ecosystem service modelling. This chapter and the following one build upon this review and the proposed guidelines and extend the state-of-the-art by discussing the development and application of two Bayesian belief network models to model the delivery of a bundle of ecosystem services, going from a specific case study (this chapter) to a regional Bayesian belief network model (chapter 4). For the in this chapter discussed case study, a pond complex located in the north-east of Flanders was chosen as study area, and more specifically, a single pond located in the area. By developing a Bayesian belief network model to model the delivery of ecosystem services by a single pond, the effect of different pond management practices on ecosystem service delivery can be assessed. This chapter predominantly focusses on the potential of Bayesian belief networks to facilitate cross-disciplinary communication for knowledge integration and the potential of Bayesian belief networks to support decision making. Several risks that are associated to the use of Bayesian belief networks in this context are highlighted as well.

This chapter is based on:

Landuyt, D., Lemmens, P., D'hondt, R., Broekx, et al., 2014. An ecosystem service approach to support integrated pond management: A case study using Bayesian belief networks - Highlighting opportunities and risks. Journal of Environmental Management 145, 79-87.

3.1 Introduction

Freshwater ponds were selected as study object because they are multi-functional ecosystems that provide a broad set of social, ecological and economic benefits for human well-being (IUCN, 1997; Bekefi and Varadi, 2007; EPCN, 2007; Downing, 2010). Typical ES of pond systems include fish production, water supply, nutrient retention, carbon sequestration, habitat support and recreational use (EPCN, 2007). Despite the high potential of ponds for the provisioning of multiple services, evaluations of management practices typically focus on a limited number of services, such as fish production, whereas other benefits are frequently overlooked (Pechar, 2000). More recently, the awareness of the importance of social and ecological aspects of pond management is rapidly growing, amongst others through the implementation of the common fisheries policy of the European Union, which strives towards sustainable aquaculture, and the Strategic Plan for Biodiversity 2011-2020, which aims to stop biodiversity loss by 2020 (UNEP/CBD, 2010). Currently, there is a strong need to take into account the multi-functionality of pond ecosystems during the development of management plans. Models and decision support tools are useful instruments to guide the development of such management plans. Although several studies have been conducted on multi-functionality of pond systems (Céréghino et al., 2010; Kloskowski, 2011), integration of this multi-disciplinary knowledge into practical management suggestions is rarely done.

In the past, several decision support systems have been specifically designed to aid the development of management programs for freshwater ponds and lakes (e.g. Gawne et al., 2012; Gutiérrez-Estrada et al., 2012). Although these tools have proven to be promising in suggesting alternative management practices during adaptive pond management, they generally focus only on one or a very limited number of objectives. The majority of benefits, especially the less tangible ones, are frequently omitted, which may lead to wrong, ill-informed decisions. An approach that takes into account ES, as mentioned by Soto et al. (2008), can tackle this problem due to its ability to identify, model and assess a more encompassing set of benefits associated with ecosystems. This can guide pond management towards a more balanced delivery of economic, social and ecological benefits, where benefits are optimised and trade-offs between benefits are revealed. Cost-benefit analysis (CBA) is a convenient method to put the ES approach into practice (Newton et al., 2012). CBAs include both costs associated with management practices and benefits associated with ES delivery. As part of the benefits of ES delivery can be expressed in monetary terms, costs and benefits can be compared directly and management decisions can be optimised towards more cost-effective ES delivery. These CBAs have been referred to as environmental CBAs by Atkinson and Mourato (2008).

By developing BBNs, as the ones discussed in the previous chapter, CBAs can be operationalised to assess the cost-effectiveness of alternative pond management practices. Advantages associated to the use of BBNs in this context include the ability to integrate multiple knowledge sources, such as, literature data, empirical data and expert knowledge and the ability to account for uncertainties. As management of natural systems is inextricably linked with uncertainties, knowledge on uncertainties associated with particular management outcomes and the ability to account for them in a CBA is extremely valuable (e.g. Bianchini and Hewage, 2012; Karmperis et al., 2012). Although the importance of risks in environmental management is widely recognised, explicit consideration of uncertainties in environmental CBAs is currently limited (e.g. Ticehurst et al., 2007; Barton et al., 2008).

3.2 Methods

3.2.1 Study area

The pond complex 'Vijvergebied Midden-Limburg', located in the north-eastern part of Belgium (Figure 3.1), was selected as study area. The pond complex comprises more than 1000 shallow lakes and ponds of which many originate from the extraction of iron ore and peat (Lemmens et al., 2013). The area is well known for its high ecological values, which largely results from extensive management of the ponds during past decades. Recent intensification of fish farming activities has resulted in considerable ecological degradation of the ponds in the region and has led to an important loss of biodiversity. The present study focusses on ES delivery of a single pond in this pond complex, using data for model development that were gathered from several ponds in the pond complex. A detailed description of the study area can be found in the work of Lemmens et al. (2013).

The current pond management strategies in the region can be classified into three major types. A number of ponds are managed for purposes of nature conservation (NCM), some ponds are used for extensive fish farming (EFF) and an important number of ponds are used for intensive fish farming (IFF). Major differences among the considered management scenarios include the level of shoreline complexity, the

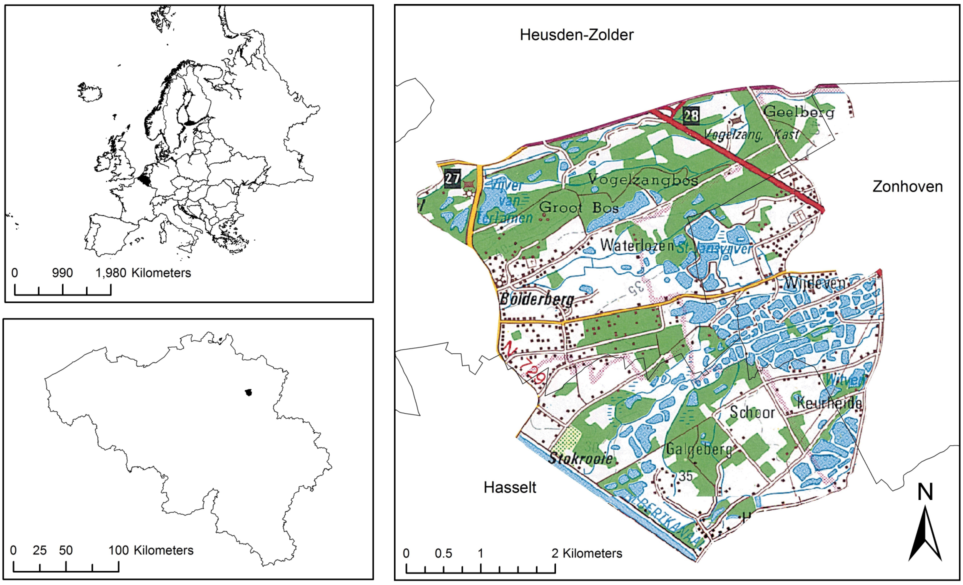


Figure 3.1: Pond complex 'Midden-Limburg', located in the northeast of Belgium, in Western Europe

initial stocking of fish (benthivores, planktivores and piscivores), the use of industrial fish feeds, and accessibility for recreational activities. In all management types, fish is harvested during pond drainage. Ponds that are managed for purposes of nature conservation are drained annually in autumn and refilled in early spring. This rather drastic measure lowers the fish density and the nutrient load and improves the transparency of the water, which promote plant and macro-invertebrate biodiversity in the ponds (Van de Meuter et al., 2008). After refilling, these ponds are stocked with low densities of planktivorous and benthivorous fish (0-30 $kg.ha^{-1}.year^{-1}$). A considerable number of ponds under nature conservation management receive no fish stocking. Ponds in use for extensive fish farming are occasionally drained (approximately every two or three years) and are initially stocked with a moderate density of planktivorous, benthivorous and piscivorous fish (30-80 $kg.ha^{-1}.year^{-1}$). Additional fish feeds are not used in nature conservation management and extensive fish farming management. Ponds in use for intensive fish farming are annually drained in autumn and are stocked in spring with high densities of planktivorous and benthivorous fish (100 $kg.ha^{-1}.year^{-1}$). Industrial feeds are used to increase fish production (approximately 1400 $kg.ha^{-1}.year^{-1}$). Each management type has fixed and variable financial costs. Fixed costs basically comprise the costs related to the maintenance of the pond (e.g. reparation of dykes, silt removal, mowing of vegetation), whereas variable costs are closely related to fish stock management (stocking densities, industrial feeds, fish harvesting). The annual fixed management costs have been estimated to amount to €778, €558 and €338 per hectare for IFF, EFF and NCM, respectively (Lemmens, unpublished data).

3.2.2 Selection of ecosystem services

In the present study, the selection of ES was based on the relevance of the services for the study area, whether or not their delivery can be altered by the considered management strategies, as well as on data and knowledge availability. Based on the CICES-BE classification (Turkelboom et al., 2014), five ES that fulfilled all criteria were selected: fish production, water quality regulation through nitrogen retention and three interlinked cultural services, including both use and non-use values. Table 3.1 provides a detailed overview of the selected services and their CICES classification. Aside from the cultural services, each ES is assessed through a different indicator. The four selected cultural services were jointly assessed with a willingness-to-pay indicator per household. Supporting services, as defined by the MEA (2005), are not taken into account to avoid double counting. Note that only one regulating service is being considered, whereas others may be of similar importance for the region (e.g. regulation of water quantity and avoidance of flooding; regulation of water quality besides nitrogen retention). This needs to be considered when interpreting the results. Biodiversity is also not included as an ES in this study. Biodiversity is in part valued through the monetary valuation of the cultural ES. Nevertheless, outcomes of ES studies should be complemented with biodiversity conservation aims to support final management decisions as only the utilitarian value of components of biodiversity can be inferred by monetary valuation (Swift et al., 2004).

3.2.3 System conceptualisation

The system being modelled was defined as a pond with a surface of 1 ha. Although no ponds with exactly this surface exist, 1 hectare was chosen for simplicity. Most available measurements were already expressed in a per hectare unit or could be easily rescaled. Also stakeholders were more confident to express their knowledge in per hectare units.

Table 3.1: An overview of the selected ecosystem services, their classification within CICES-BE (Turkelboom et al., 2014) and the applied indicator.

Section	**Division**	**Group**	**Class**	**Service and indicator**
Provisioning	Nutrition	Biomass	Freshwater plants and animals for food	**Fish production**, expressed as fish mass gain multiplied with its market value (€.ha^{-1}.year^{-1})
Cultural	Physical and intellectual interactions with biota, ecosystems, land- and seascapes	Natural environment suitable for outdoor activities	Areas for non-excludable outdoor activities	**Cultural value**, expressed as willingness-to-pay for improvements in the conditions of the pond (€.household^{-1}. ha^{-1}.year^{-1})
			Areas for excludable outdoor activities	
	Spiritual, symbolic and other interactions with biota, ecosystems, land- and seascapes	Spiritual and/or emblematic	Landscapes and species with cultural and symbolic values	
Regulation and Maintenance	Mediation of waste, toxics and other nuisances	Soil and water quality regulation	Nutrient regulation	**Nitrogen retention**, expressed as the amount of nitrogen retained by the pond through denitrification multiplied with its avoided abatement cost (€.ha^{-1}.year^{-1})

3.2.4 Model development

Model development was carried out according to the guidelines described by Marcot et al. (2006). First, an influence diagram was composed to describe the expected cause-effect flows of service provision of a single pond. This causal network was developed based on a consultation of researchers involved in ecological research in the study area (for an overview, see Appendix E). A second group of independent experts (Appendix E) were consulted for reviewing the structure of the model. After evaluation, final model adjustments and final model approval, the CPTs of the model were quantified. The quantification of the CPTs was mainly based on gained expert knowledge obtained from recent scientific research in the study area (Lemmens et al., 2013). When available, site-specific empirical relations and site-specific data were preferred over expert knowledge to populate the model's CPTs, through Monte Carlo simulations and model learning, respectively. To populate the CPTs that underpin the ecological relations in the model, the experts that reviewed the model structure were consulted via an online questionnaire. The final model was converted into a Bayesian decision network (BDN) by adding a decision node, representing the different management scenarios, and a utility node, representing the sum of the monetary value of the provided services minus the management costs, for each management scenario. Model implementation was carried out in Netica (Norsys Software Corporation, 1998). A graphical representation of the operational model is provided in Figure 3.2. A list of variables that were included in the model is provided in Appendix B.

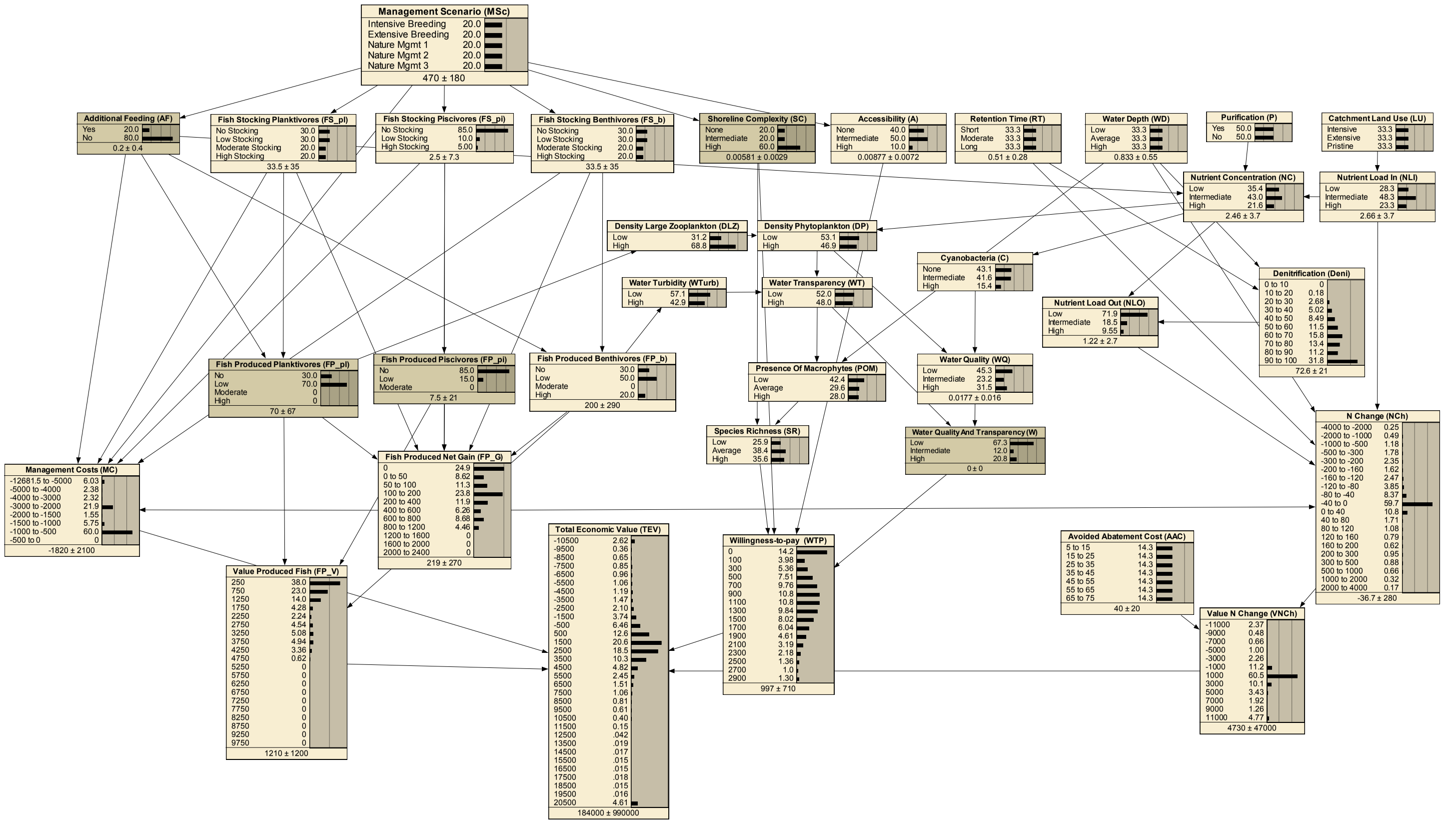


Figure 3.2: Bayesian belief network model for environmental cost-benefit analysis. The model comprises a decision variable which entails several potential management scenarios, management and system defining variables, variables denoting ecosystem functions and services and a variable denoting the total economic value to define the cost-effectiveness of management practices in delivering ecosystem services. This model layout enables analysing costs and benefits related to pond management taking into account the delivery of three ecosystem services.

3.2.5 Process description

To populate the CPTs in the developed BBN, different knowledge sources were exploited, ranging from data and existing models to literature and expert knowledge. This section briefly discusses the development of all components of the network, including scenario definition, fish production modelling, cultural value modelling and nitrogen retention modelling.

Management scenarios

A decision node was implemented in the model to evaluate and compare the considered scenarios in terms of ES delivery and management costs. This node, in which each management scenario is represented as a separate state, was coupled with the manageable variables to represent the influence of management on these variables. Figure 3.3 illustrates how the considered scenarios were implemented in the BBN.

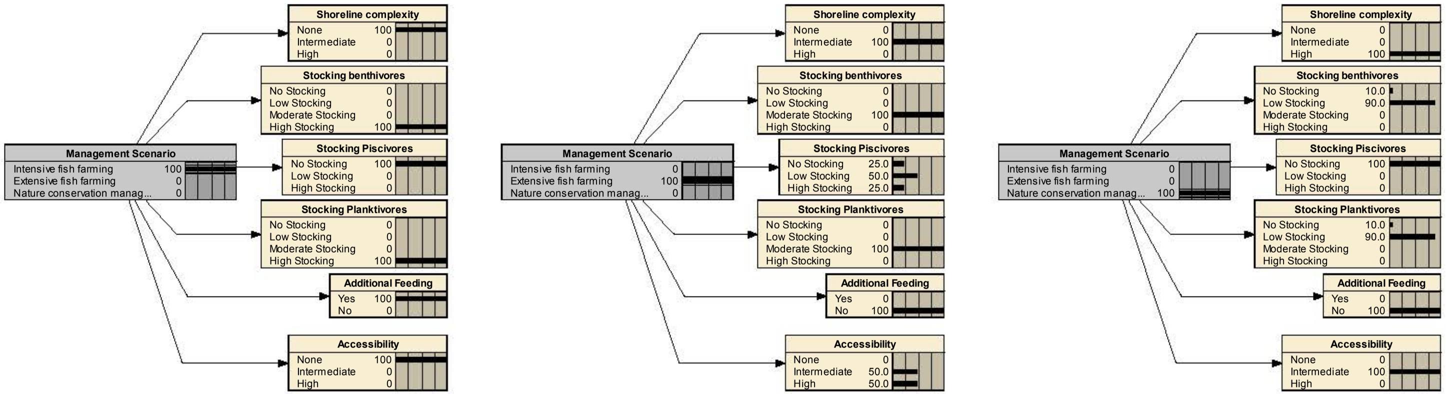


Figure 3.3: The implementation of the management scenarios and their influence on the individual management variables: additional feeding, stocking of planktivores, stocking of piscivores, stocking of benthivores, accessibility and shoreline complexity.

Fish production

Fish farming activities in the area comprise the production of a broad range of fish species. The effect of fish stocking and the use of fish feeds on fish production was determined based on empirical data from previous research in the study area (Lemmers et al., 2012) and on knowledge obtained from local fish farmers (for an overview of the consulted fish farmers, see Appendix E). To model fish production and to facilitate the interpretation of the results, different species were grouped into three main functional groups (planktivores, benthivores and piscivores, with a main feeding mode focussed on zooplankton, sediment-inhabiting worms and insects, and fish respectively). This classification is important as species from the same functional group have similar ecological effects on pond ecosystem functioning and their production demands similar management measures. The annual fish biomass production per hectare is strongly determined by management factors such as fish stocking and the use of additional industrial fish feeds. The effect of fish stocking and the use of fish feeds on fish production, was determined based on empirical data from previous research in the study area and on knowledge obtained from local fish farmers. A ten-fold biomass increase for benthivorous fish with additional feeding (based on fish farmer experiences) and a 1.5-fold increase for all functional fish groups without the use of feeds (based on scientific experiments) was assumed (Lemmers et al., 2012). The derived empirical equation (Equation 3.1) is represented below. With F_h = harvested fish biomass ($kg.ha^{-1}.year^{-1}$), F_s = stocked fish biomass ($kg.ha^{-1}.year^{-1}$) and AF = provision of additional feeds (one in case additional feeds are provided, zero in case not). Note that this empirical equation only holds for stocking densities in between the range of the currently applied stocking densities. For higher stocking densities a decrease in production rate can be expected (Lemmers et al., 2012).

$$F_h = F_s(1.5 + 8.5 * AF) \tag{3.1}$$

The economic valuation of fish production is based on current market prices derived from face-to-face interviews with local fish farmers. Although prices can show some variation among years and with fish body size, fixed market prices of €4 kg^{-1} for benthivorous and planktivorous fish and €10 kg^{-1} for piscivorous fish were used. In addition to these benefits, also fixed and variable managements costs were taken into account (discussed in section 3.2.1). As no information was available on uncertainties associated with management costs, these uncertainties were not included in the model. The cost of providing additional feeding, the effect of fish feeding on production and the cost of fish stocking was derived from interviews with local fish farmers. A net gain of 1 kg fish mass per 1.4 kg food at a price of €0.75 kg^{-1} was the rule of thumb most fish farmers in the study area applied. Although similar fish feed conversion ratios have been reported for carps in other studies (e.g. Mungkung et al., 2013; Przybyl and Mazurkiewicz, 2004), ratios up to 3 and higher have been found as well (e.g. Lemmers et al., 2012; Jabeen et al., 2004). 1.4 can,thus, be regarded as a lower bound given that high quality feed is provided. The cost of initial stocking of fish, reported by local fish farmers, was €3.5 kg^{-1}, €4 kg^{-1} and €0.9 fish^{-1} for stocking of benthivorous, planktivorous and piscivorous fish, respectively.

Cultural value

The cultural value people attach to improvements in the ecological status and accessibility of the ponds in the study area was determined using a stated preference choice experiment (CE) (Hoyos, 2010; Liekens et al., 2013a; De Valck et al., 2014). Biodiversity, water quality, shoreline complexity and accessibility of the pond were the main variables included in the CE. Biodiversity, water quality and shoreline complexity were selected in light of the three objectives of the Water Framework Directive: biological quality, water quality and hydromorphology. The water quality and biological quality classifications used by the Flemish Environmental Agency (VMM) were used and, following Hanley et al. (2006), divided into three classes: low, intermediate and high. The classification adopted for assessing accessibility for soft recreation distinguished between the presence of walking and biking trails (no, restricted and widespread). To account for scale effects, number of ponds (1 or 50) was also included in the CE. The CE was carried out as a survey and reached in total 2994 respondents. Respondents had to choose multiple times between three alternative scenarios of which one of them was the status quo. This status quo scenario was a pond with average water quality, no shoreline complexity and no access for walking or biking. Each scenario was defined by a particular combination of pond characteristics and, except from the status quo, was associated with a potential per household water tax increase. The respondent could, subsequently, choose either for no change or for a tax increase they are willing to pay for one of the suggested pond improvements (see also Figure D.1).

The results showed a high willingness-to-pay (WTP) for an improvement in one pond, but the WTP per hectare was strongly diminishing when considering 50 ponds. Considering these budget constraints reflected by the fact that people want

Table 3.2: Parameter estimates and marginal willingness-to-pay values (€.household^{-1}.ha^{-1}.year^{-1}) for the attributes of the willingness-to-pay function, estimated using an error components logit model. Significance levels are denoted by ‡(1%), †(5%) and *(10%).

Attributes and interactions	Model result	WTP	Confidence interval
Price	-0.01465‡	/	/
Average shoreline complexity	0.197627†	0.006751	0.003547; 0.010966
High shoreline complexity	0.217357‡	0.007425	0.004088; 0.011740
Limited availability of walking trails	0.435792‡	0.014888	0.009788; 0.023816
Full availability of walking trails	0.387062‡	0.013223	0.008468; 0.020896
Average species richness	0.313036‡	0.010694	0.006663; 0.017144
High species richness	0.323459‡	0.011050	0.006848; 0.017536
Good water quality	0.859976‡	0.029379	0.020526; 0.045707
Very good water quality	1.006895‡	0.034398	0.023729; 0.054184
Size (ha)	0.001776*	/	/
Distance (log (km))	-0.14722	-10.0475	-14,8277; -5.2664
Income (€)	0.000588‡	0.000020	0.000013; 0.000031
Member of nature organisation (%)*size(ha)	1.878517‡	0.064175	0.038890; 0.101870

to invest less per hectare when more ponds are considered, we adapted the WTP formula by including the size attribute in the equation. Based on this new equation and assuming that every hectare of the same improvement is equally preferred, the WTP-formula was down-scaled in order to estimate an household's marginal WTP per extra hectare of pond surface. The obtained WTP summarises a respondent's household's willingness-to-pay for quality improvements of a single pond (1 ha). The coefficients of the obtained value function are provided in Table 3.2. Willingness-to-pay values derived from the regression model's coefficients (expressed in €.ha^{-1}.year^{-1}) are provided in the third column of Table 3.2.

WTP also depends on socio-economic characteristics of the respondent, such as, income and whether or not the respondent is a member of a nature organisation. To correct the WTP estimates for these factors, respondents' socio-economic characteristics were also recorded in the survey. This way, socio-economic aspects could be included in the WTP equation and could be used to correct WTP estimates based on the socio-economic characteristics of the population of Flanders (e.g. average income). A final variable included in the valuation function was distance to the pond complex. This variable allows to define a market extent without the use of artificial boundaries (Liekens et al., 2013a). As the WTP of the valuation function converged to zero for travel distances above 1 km, the market was limited to the households living in a 1 km-buffer around the study area (Figure 3.1). The total monetary cultural value of the pond was obtained by multiplying the household's average WTP with the number of households within the market extent. To account for uncertainties related to the coefficients of the WTP equation, a Monte Carlo simulation (5000 samples) was carried out based on the mean value and standard deviation of the estimated coefficients in the WTP function (Table 3.2). This resulted in a relatively large standard deviation (+/- 60%) on the estimated average WTP values.

As the WTP depends on pond biodiversity and water quality, both aspects, as well as their determining processes, were included in the model. These determining processes were modelled based on general expert knowledge, gathered through an online expert questionnaire (for an overview of the consulted experts, see Appendix E). To limit the burden of this questionnaire, we simplified the ecological processes considerably in the BBN. The simplified model structure was defined based on literature and expert knowledge.In the survey, experts were asked to provide conditional probabilities, in steps of 25%, for each variable in the model and, on top, were asked to provide a degree of confidence in their estimates. This method was adapted from the elicitation approach described by Pollino et al. (2007b) which was based on the guidelines of Morgan and Henrion (1992). Knowledge of multiple experts was eventually aggregated in the model based on the linear opinion pool approach (Clemen and Winkler, 1999). More information and an example question of this survey are provided in Appendix A.

Nitrogen retention

Nitrogen retention in the pond system was approximated by summing nitrogen assimilation in fish biomass and denitrification of nitrogen in the water column. Equation 3.2 provides the considered nitrogen balance.

$$N_{balance} = N_{outflow} - N_{inflow} = N_{fishfeeds} - N_{denitrification} - N_{harvestedfish} \quad (3.2)$$

Nitrogen assimilation in fish biomass was derived from the modelled fish biomass gain and an average fish (wet biomass) nitrogen content of 2.6% (Ramseyer, 2002). Denitrification in the water column depends on retention time and pond depth, and was modelled based on a regression formula derived from a meta-analysis performed by Seitzinger et al. (2006). This formula predicts percentage nitrogen removal based on retention time and pond depth (Equation 3.3). Nitrogen removal in the water column is additionally dependent on the pond's actual nitrogen concentration, which is determined by additional feeding, management practice, and nitrogen inflow. While the nitrogen content of the inflow was derived from in-situ measurements, nitrogen input from additional feeding was determined based on conventional feeding amounts and feed nitrogen contents. Total nitrogen removal was determined by comparing the nitrogen concentration of the inflow with that of the outflow.

$$N_{removed}(\%) = 88.\left(\frac{Water\ depth(m)}{Residence\ time(year)}\right)^{-0.368} \tag{3.3}$$

For the monetary valuation of nitrogen removal, the avoided abatement cost method was used, a valuation method suggested by Broekx et al. (2013b) for monetary valuation of nitrogen removal in surface waters in Flanders. As local estimates for the study area were not available, both a high (€74 $kg^{-1}N$) and a low (€5 $kg^{-1}N$) estimate were used (Cools et al., 2011). Values were derived from a cost-effectiveness analysis on nitrogen removal in agriculture, households and industry as required for the implementation of the EU Water Framework Directive. The applied costs refer to the marginally most expensive measures that were selected in the first river basin management plan. It reflects the existing willingness to invest in reducing nutrient loads entering the river systems. The high estimate (€74 $kg^{-1}N$) reflects the average marginal cost estimates of the entire Flemish Region. As the study area is situated upstream and less efforts are required to reach water quality targets, a lower estimate (€5 $kg^{-1}N$) was also applied based on marginal abatement cost levels typically required in upstream areas. Marginal avoided abatement costs are highly variable and depend on the nutrient load, the available technologies and the targets to be reached. Although most studies in the European Union (e.g. Hautakangas et al., 2014; Grossmann, 2012; Börjesson, 1999) report values in the lower end of this range, this range was assumed valid for Flanders due to the problematic nutrient pollution in the region and the high investment levels necessary to reach these targets. As the most cost-effective measures (e.g. large scale waste water treatment plants) are already implemented, more expensive measures (e.g. reduced fertilizer use, reduction in number of pigs/cattle, sewage connections to more remote houses) are needed to reach nutrient targets in Flanders. Other regions such as Sweden and Denmark that are facing similar issues also report estimates close to €74 $kg^{-1}N$ (Elofsson, 2010). A uniform probability distribution between both extremes was used as prior probability distribution for the 'Avoided abatement cost' node in the network.

3.2.6 Analysis of model results

Qualitative assessment of model results

A qualitative assessment of the model results is carried out based on the intermediary ES production nodes in the BBN. These nodes express ES production in biophysical terms (kg.ha^{-1}.year^{-1}), with the exception of the cultural value, which is measured directly in monetary terms (€.ha^{-1}.year^{-1}). As aggregation of these biophysical quantities per scenario is not possible, the delivery rates for each service are normalised between no production (0%) and maximum production (100%) and are compared in radar plots for each management scenario. This way, ES delivery can be compared qualitatively among the considered scenarios.

Quantitative assessment of model results

As uncertainties were taken into account to estimate the monetary value of each delivered service, a probabilistic cost-benefit analysis was carried out for each scenario. In a probabilistic environmental CBA, uncertainties associated with ES delivery are taken into account, while monetary values are used to express the relative importance of the individual ES. To visualise probabilistic CBAs, cumulative probability distribution functions (CDF) are frequently used (Karmperis et al., 2012). CDFs can be easily derived from discrete probability distributions by Equation 3.4.

$$CDF_X(x) = P(X \leq x) = \sum_{i=0}^{x} P_X(i) \tag{3.4}$$

The slope of a CDF visualises the uncertainty associated with the outcome of a particular scenario. Steep curves denote low uncertainty, while flat curves denote high uncertainty. The position of the curve indicates the profitability of a particular scenario. Scenarios are considered more profitable the more right their curves are located. Another advantage of cumulative probability curves is that differences in interval lengths do not bias the representation, while it does using standard probability mass functions.

To test the model's sensitivity to the selected set of ES, the model was ran several times considering three different sets of ES: considering only fish production as a relevant ES, considering both fish production and cultural services, and taking into account all three services. These three sets were composed in accordance with the spatial distribution of the ES beneficiaries ranging from local fish farmers to regional citizens.

Sensitivity analysis

As discussed by Bennett et al. (2013), a wide range of approaches are available to evaluate the performance of environmental models. While quantitative approaches are generally more objective, qualitative approaches are especially valuable in data-poor situations where models are learned based on small datasets or expert knowledge. Under these circumstances, test data sets are generally not available, which impedes the use of quantitative model validation approaches (Bennett et al., 2013).

To assess the sensitivity of the model's output node (ES delivery node) to changes in another node X, variance reduction (VR) values are calculated. $\mathrm{VR}_{ES}(\mathrm{X})$ expresses the reduction in variance of the model's output node (ES) caused by instantiation of node X. Thus, for each ES delivery node, variance reduction values can be calculated for all nodes in the model by Equation 3.5. With s representing the states of the output node. To enhance comprehensibility, variance reduction values are generally rescaled to relative variance reduction values, ranging between 0 and 100 percent. Relative variance reduction calculations are performed by Netica, the applied BBN software package.

$$VR_{ES}(X) = V(ES) - V(ES|X) = \sum_s P(s) * (s - E[ES])^2 - \sum_s P(s|X) * (s - E[ES|X])^2 \tag{3.5}$$

3.3 Results

3.3.1 Qualitative and quantitative assessment of ecosystem service delivery

The radar plots in Figure 3.4 qualitatively represent ES delivery under the three considered management strategies. The expected ES delivery is positive under all management scenarios, with only nitrogen retention being slightly negative under IFF management. This indicates that intensively managed ponds discharge more nitrogen through their effluent than they have received from inflowing water. NCM and EFF seem to be associated with the most balanced and optimal ES delivery when each of the ES are considered to be equally important. Figure 3.4 additionally

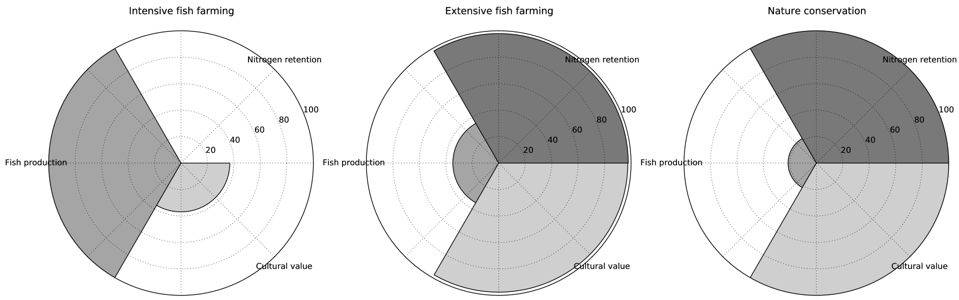


Figure 3.4: Qualitative analysis of ecosystem service delivery under the considered management scenarios.

suggests complementarity between IFF at the one hand and EFF and NCM at the other hand due to a clear trade-off between fish production and the other two considered services. This qualitative assessment does not provide information on the relative importance of each service, nor on the management costs or uncertainties associated with the delivery of ES.

3.3.2 Monetary assessment of ecosystem service delivery

The probabilistic results of the CBA, considering all three ES, are shown in the top panel of Figure 3.5. As can be seen in the plot, the curve of the NCM scenario is located rightmost or, in other words, NCM seems to be the most profitable scenario. The curves of the IFF and EFF scenario cross each other, indicating less clear differences in profitability among these scenarios. Under the current selection of ES, both the expected net benefit and the probability of a positive net benefit will be higher for NCM. Taking into account uncertainties, IFF can be seen as a management practice associated with high risks. The risks associated with the expected net benefit of EFF and NCM are lower. NCM can be considered as a low risk investment. Note that the uncertainty in the model output should be seen as a minimum estimate, as not all uncertainties are known and documented and, thus, integrated in the model.

The two lower panels of Figure 3.5 illustrate the effect of taking into account fewer services. In case only fish production is considered as a relevant service, the IFF scenario stochastically dominates all other scenarios and, thus, would be considered the most profitable. Both the probability of achieving a positive net outcome (in-

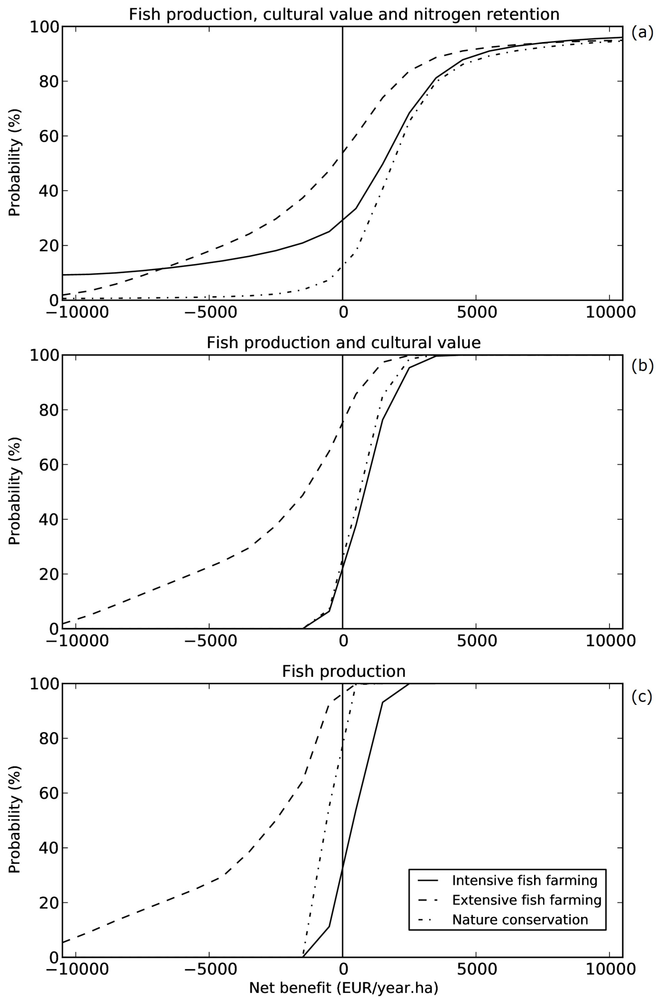


Figure 3.5: Probabilistic cost-benefit analysis of the considered management scenarios considering three different sets of ecosystem services: fish production, cultural value and nitrogen retention (a), fish production and cultural value (b) and only fish production (c). These cumulative probability distributions visualise the probability of obtaining a lower net benefit than a particular value on the x-axis. The more right the curve, the more profitable the scenario, the steeper the curve, the more certain the expected net outcome of the scenario.

tersection of the curve with the vertical line) as the probability of achieving high benefits is higher for IFF than for the other management types. When the cultural value is additionally taken into account, the curves converge, resulting in comparable expected net benefits for NCM and IFF (middle panel of Figure 3.5). The low profitability of the EFF scenario is mainly caused by the high costs related to stocking of piscivores, a typical management practice in EFF. When all three services are taken into account, the curves switch position, denoting NCM as the most profitable scenario. Both the expected net benefit as the probability of a net positive outcome is higher for NCM under this more complete scenario.

3.3.3 Sensitivity analysis

Figure 3.6 presents the top-ten most-influencing variables, determined by a sensitivity analysis of the model. As can be seen in this figure, all variables are related to the nitrogen retention process, which denotes that this process, and the way it is implemented in the model, can influence the outcome remarkably. Furthermore, none of the variables from which the CPTs were elicited by experts were listed, indicating that these variables were not of major importance for the model output. As their importance in the model is rather low, approximate estimation of the CPTs of these nodes through expert elicitation should suffice. For this purpose, the survey definitely provided sufficient information.

3.4 Discussion

3.4.1 Bayesian belief networks for decision support

Modelling the full cascade of ES delivery using both decision nodes and utility nodes and structuring knowledge to integrate poorly-documented services with well-studied ones were mentioned as one of the underutilised of BBNs in the previous chapter. This chapter clearly illustrates the potential to integrate and structure knowledge from diverse scientific domains ranging from ecology (ecological processes) to economy (ESS valuation). Also the ability of BBNs to inform decision makers based on uncertainties and the added value of these uncertainties were demonstrated. Whereas management suggestions may be clear when based on expected outcome, they may be less clear when uncertainties are taken into account. Consideration of risks associated with the outcomes of management practices is especially useful when biological systems and financial markets, which are both inextricably linked

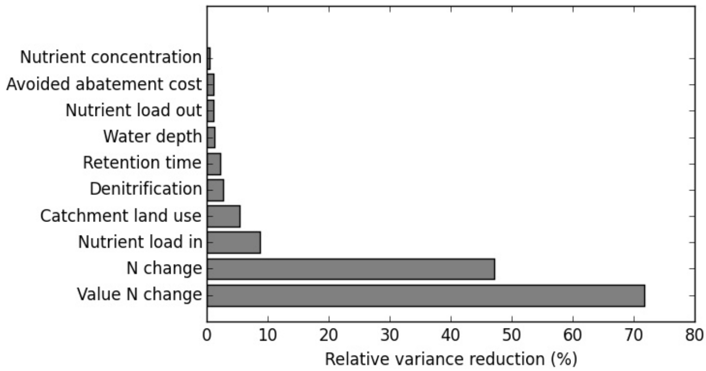


Figure 3.6: Top-ten most-influencing variables derived from the sensitivity analysis. Percentage of variance reduction (x-axis) specifies the reduction in variance of the output variable given information on the state of the node on the y-axis.

with uncertainties, are considered in a CBA. In these situations, the relevance of conventional deterministic CBAs is limited.

Yet, increased complexity is an important drawback of including uncertainties in the analysis. Although guidelines exist to support decision making based on probabilistic CBAs (Karmperis et al., 2012), end-users may encounter some difficulties interpreting them. Another important risk related to developing BBNs is using knowledge obtained from a limited amount of experts to draw general conclusions. One needs to consider that those conclusions only reflect the beliefs of the consulted experts and not necessarily the truth.

3.4.2 Exclusion of ecosystem services

Although including several services into one model is generally perceived as a strength, it may give the impression that the study takes into account all relevant services. The results clearly demonstrate the risk of accounting only for a limited set of services. While discriminating among scenarios would reveal IFF as the most profitable management when only fish production is valued, broadening the set of services tipped the balance towards more nuanced and even qualitatively opposite results. The fact that different sets of ES can change management suggestions stresses the need to try to consider a complete or balanced as possible set of ES for evaluating alternative management practices and that ignorance of poorly-studied services entails an important risk for biased recommendations that may be both qualitatively and quantitatively wrong. Considering the fact that only one regulatory service was included in the analysis, while others (e.g. water retention) may be important as well, model results will likely change when including more regulating services. Findings of previous research on the relationship between biodiversity and delivery of regulating ES (Balvanera et al., 2006) suggest that taking into account additional regulating services would promote NCM as the most profitable scenario. Although this indicates that the presented model results cannot be seen as providing final management suggestions, BBNs have the potential to contribute to more complete ES assessments as both well-studied (based on empirical data) and poorly-studied services (merely based on qualitative data) can be taken into account. Due to their modular nature, BBNs can be easily expanded to include more services when more information becomes available.

3.4.3 Upscaling and spatial configuration

As suggested in the methods section, considering the entire pond complex will probably lead to completely different outcomes for the cultural values compared to multiplying the total economic value of one pond with the total number of ponds in the complex. The inability to use the model to assess ES delivery of the entire pond complex is therefore a second important limitation of the current analysis. The causal relations in the BBN, derived for a single pond, cannot be blindly extrapolated to multiple ponds. The number of ponds and their spatial configuration will have an effect on ES, such as nitrogen retention and regulation of water quality in general. Also biodiversity, for example, would benefit from a combination of different pond management types (Oertli et al., 2002; Scheffer et al., 2006; Lemmens et al., 2013), a result that is not predictable with a model based on one pond. Upscaling of WTP values encounters similar difficulties. Although the survey considered different numbers of ponds, no mosaic scenarios, with different management practices in different ponds, were considered. Thus, people's preference for particular mosaic scenarios could not be predicted. Further research on this is needed, including identification of spatial interactions among ponds and assessing the cultural and ecological value of mosaic scenarios.

3.4.4 Monetary valuation of ecosystem services

Applying monetary valuation in ES assessment has both advantages and disadvantages (Gómez-Baggethun and Ruiz-Pérez, 2011). An important advantage is the ability to aggregate the delivery of multiple services in a common indicator which is understandable for a broad range of stakeholders. Moreover, aggregation of ES delivery to one monetary value enables consideration of management costs which, in turn, enables analysing cost-effectiveness of management practices. Although monetary valuation in many cases can deliver clear and explicit results, some disadvantages of monetary valuation need to be mentioned. As stated by Martín-López et al. (2013), there is a bias towards provisioning services which are relatively easy to quantify in monetary terms. However, in most cases, only a limited set of stakeholders benefit from these provisioning services. In contrast, regulating services generally affect the well-being of a broader range of stakeholders. These services, however, are more difficult to quantify. Thus, given the negative relationship between intensive fish production and biodiversity (Lemmens et al., 2013) and regulating services (Balvanera et al., 2006), a high yield for a limited number of stakeholders generally comes at a cost for a broader set of stakeholders.

Moreover, monetary valuation is not well-designed to quantify the intrinsic value of nature, which therefore needs to be considered aside from the economic analysis of management practices. However, blinded by the strength of an economic analysis, assessing the effects on biodiversity is frequently forgotten.

Also longterm sustainability issues are not accounted for in the presented monetary values. For example, in case a lot of ponds in the area are used for intensive fish farming, the carrying capacity of the system can be reached which may lead to ecosystem degradation in the long run. Toxic anaerobic water conditions will lead to fish mortality and, hence, to lower yields.

3.5 Conclusion and recommendations

Putting the ES approach into practice and accounting for uncertainties are important challenges for sustainable management of ecosystems. The proposed methodology to assess multiple management practices shows that both are feasible. Compared to conventional CBAs, the suggested approach of BBNs can offer valuable information on uncertainties associated with environmental management. In addition to the added value of uncertainties, the benefits of an ES approach to provide guidelines for management of water bodies are clearly demonstrated in this study. The key challenge is, however, that many ES remain difficult to monetise as their monetary valuation often requires a lot of data. As a result, they risk to be ignored in many assessments. The analysis clearly shows that inclusion or ignorance of specific ES strongly affects the model results and the recommendations that can be drawn from them. Although the analysis is still far from complete as only a limited set of services is accounted for and spatial interactions are not taken into account, it already illustrates the potential of BBNs to include different types of ES into a probabilistic CBA.

4 A regional application of Bayesian belief networks for ecosystem service modelling

The previous chapter discussed an application of Bayesian belief network models to assess ecosystem service delivery of a specific ecosystem. The model enabled assessing the effects of a set of specific management options on ecosystem service delivery. Although several strengths of Bayesian belief networks have been highlighted in this chapter, difficulties to scale up the results to assess ecosystem service delivery at a broader scale were mentioned as well. To develop models that are regionally applicable in Flanders, a different approach is needed. This new approach requires using data that are representative for the entire Flemish region, a different way of identifying and delineating entities that can be seen as separate ecosystems and a focus on models that operate on input data with a regional coverage. This chapter successively discusses the state-of-the-art of regional ecosystem service models, proposes a system conceptualisation which enables the use of Bayesian belief networks for regional ecosystem service assessment and describes the development of models for different ecosystem services, relevant within the Flemish context. Moreover, the use of Bayesian belief networks to identify drivers that determine ecosystem service delivery and to reveal interactions among services is illustrated.

4.1 The state-of-the-art of regional ecosystem service assessment

As mentioned earlier in this work (section 1.1), since the adoption of the EU biodiversity strategy, EU member states are encouraged to assess, map and report the delivery of ES in their national territory (target 2, action 5). The main objective of action 5 is that national accounts can be used to support decision making at the national level and the EU level (Maes et al., 2012). As a first step, EU member states are encouraged to provide national ES accounts. However, also interactions among services, such as, synergies and trade-offs need to be investigated to gain more insights. To do so, assessment methodologies and ES models are being developed. Chapter 1 provided a generic overview of the methods that are currently being used to model the supply, the demand and, eventually, the delivery of ES at the regional scale. Results are generally provided as ES maps although non-spatial methods exist (e.g. Broekx et al., 2013b). The advantage of using maps is that they enable accounting for spatial heterogeneity of ES delivery. Important spatial drivers that give rise to this spatial heterogeneity are, amongst others, soil type, land use and population density, drivers that are highly spatially heterogeneous.

As discussed in section 1.3, a broad range of methodologies and tools have been developed for ES assessment. However, not all these techniques are suitable for regional ES assessments. Generally, spatial, grid-based models are used for regional accounting (e.g. Maes et al., 2012; Kareiva et al., 2011; Bagstad et al., 2011). Currently, the most popular methods are those based solely on land cover (e.g. Burkhard et al., 2009), a proxie for which coarse data are globally available (e.g. MODIS land cover (Friedl et al., 2002), CORINE (Europe only) (Bossard et al., 2000), GLC2000 (Bartholomé and Belward, 2005)). However, poor performance of these models, as shown by Eigenbrod et al. (2010), suggests that more advanced models are needed. Applying already available tools such as InVEST (Kareiva et al., 2011) might be an option. However, differences in data availability require different modelling techniques and different national contexts often require a focus on different services. For example, while regulation of water flow is an important service for both Spain and Belgium, the former country will prefer models that pay more attention on drought prevention, while the latter needs models that focus predominantly on flood prevention. For more detailed ES assessments, more advanced methods, that are adapted to local data and the local context, are needed. Also in Flanders, specific ES models are being developed in the context of different projects: NARA-T (https://www.inbo.be/nl/natuurrapport-2014); the Nature Value Explorer (Broekx et al., 2013b) and ECOPLAN. Although the quality of these models is hard to judge due to the absence of validation data, Van der Biest et al. (2015) pointed at large discrepancies between the results of these models and the results of generic land use-based assessments. Assuming that detailed models based on local data perform better than generic land use-based assessments, these findings suggest that detailed models clearly have an added value for ES assessments in Flanders. The majority of models that are currently being used in Flanders can be classified as GIS-based models that combine available spatial datasets with knowledge extracted from literature, existing models and expert knowledge.

An important drawback of these models is that they cannot account for uncertainties and that they are only suitable for mapping exercises and less suitable for system exploration to enhance system understanding. Limited possibilities to integrate models for individual services into one integrated model impedes, for example, analysing interactions among services. Only through pairwise comparison of ES maps, obtained through running the individual models, ES interactions can be assessed (Mouchet et al., 2014). A second important weakness of these models is the low model transparency which complexifies model evaluation. Model evaluation is, however, very important to check the vast amount of assumptions that are frequently included in GIS-based models. The ability of BBNs to account for uncertainties, to model multiple services simultaneously and to integrate expert knowledge and assumptions transparently makes these models useful tools to complement existing ES assessment strategies in Flanders.

4.2 Methods

4.2.1 Study area

The Flemish region, located in the northern part of Belgium, is an industrialised region, characterised by a high population density and a high degree of urbanisation (Figure 4.1). Regional population density has grown to 472 citizen/km^2 (Statistics Belgium, 2014). Currently, land use in Flanders is dominated by agricultural land (54%) and urban areas (30%). Other important land use types in the context of ES delivery include forests (10%), water (2%), semi-natural grasslands (1%), heathland (0.7%) and wetlands (0.2%) (Poelmans and Van Daele, 2014).

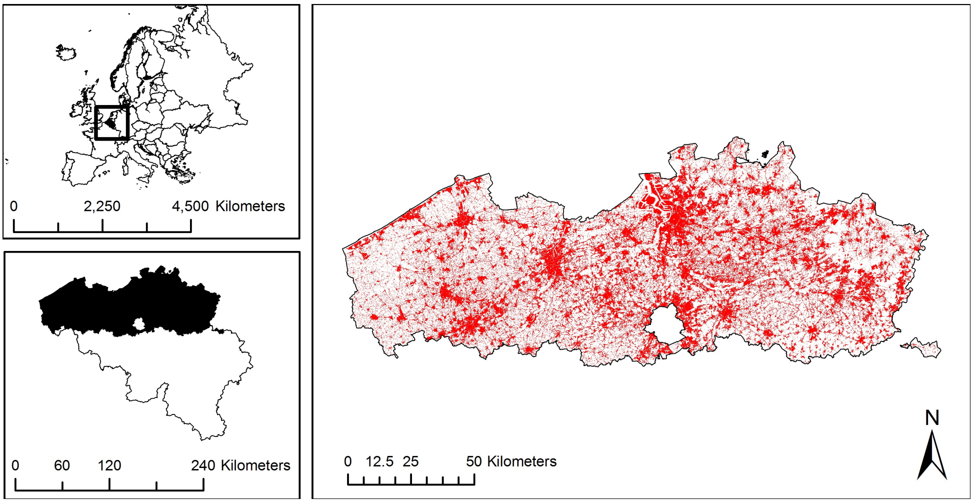


Figure 4.1: The location of Flanders within Europe (top left) and Belgium (bottom left). The map on the right represents the extent of urban area in Flanders (Poelmans and Van Daele, 2014).

4.2.2 Selection of services

As the aim of this chapter is to illustrate the applicability of BBNs to assess ES delivery and trade-offs and synergies at the regional scale, rather than to provide a full picture of ES delivery in Flanders, not all services that are relevant within the Flemish context were taken into account. Only 6 out of the 41 classes that were considered in the Belgian classification of CICES (Turkelboom et al., 2014) were taken into account. The considered provisioning services include food production, wood production and drinking water production. Although the inclusion of drinking water production as a provisioning service is frequently debated due to its abiotic nature (Haines-Young and Potschin, 2013), the service was included as a provisioning service in this study. The considered regulating services include air quality regulation, global climate regulation and soil formation. The availability of data and modelling procedures and the potential to model the service using BBNs determined the selection of services considered in this chapter. Although more services could have been included based on these selection criteria, a set of six services that include both regulating and provisioning services was considered sufficient to illustrate the applicability of BBNs. Moreover, if more services would have been included, the model would have become too complex and difficult to run on a standard computer. Table 4.1 provides an overview of the considered services, their classification within

CICES-BE (Turkelboom et al., 2014), the service names used in this book to refer to them and the indicators or units that are used to express the amount that is being delivered. Although modelled indicators not always fully describe the service, service names and indicator names are both used to refer to the modelled indicator throughout this book.

As shown in Table 4.1, both monetary and non-monetary units are used to express the amount of services being delivered. Monetary values were only used for the provisioning services wood production and food production due to the clear link between yearly yield and yearly economic benefits. For the other services biophysical indicators are used.

4.2.3 System conceptualisation

As discussed by Hein et al. (2006), prior to model development, the system being modelled needs to be delineated. In the previous chapter, an object-oriented approach was followed. A pond, with a size of one hectare, was chosen as the entity on which the developed model operated. Although using a similar object-oriented approach for regional model development is possible, for example, by subdividing the land into individual land parcels, landscape elements or patches of similar land use, most existing ES models use arbitrary boundaries, such as, a regular grid and interprete individual grid cells as seperate systems that deliver ES (e.g. Kareiva et al., 2011). This popularity is mainly related to the flexibility of a grid-based approach. In the ES context, next to ecological boundaries (as suggested above), also administrative boundaries may play a crucial role as these often delineate zones wherein people that benefit from the service live (Figure 4.2). A grid cell can be interpreted as a common divisor of all potentially applicable land divisions (e.g. ecological and administrative boundaries). Thus, the grid-based approach avoids the problem of choosing between different ways to subdivide the system. In this and the following chapters, the terms cell and pixel are both used to refer to a grid cell.

The main disadvantage of a grid-based approach is that some information is lost. While the size of a system might influence the amount of services it delivers, size information is lost when the land is subdivided into grid cells with an equal size. Another disadvantage, specifically related to BBNs, is that the use of grid-based modelling instead of field-based modelling may generate problems related to scaling up the uncertainity associated to individual grid cell values to an estimate of the uncertainty attached to the total regional ES delivery (Canters, 1997). The latter

Table 4.1: An overview of the selected ecosystem services, their classification within CICES-BE (Turkelboom et al., 2014) and the applied indicator.

Section	**Division**	**Group**	**Class**	**Service and indicator**
Provisioning	Nutrition	Biomass	Terrestrial plants, fungi and animals for food	**Food production**, expressed as net income from crop production (€.ha^{-1}.year^{-1})
		Potable water	Groundwater for drinking	**Drinking water production**, expressed as infiltration rates (mm.year^{-1})
	Materials	Biomass	Fibres and other material from plants, algae and animals for direct use or processing	**Wood production**, expressed as net income from wood production (€.ha^{-1}.year^{-1})
Regulation and maintenance	Maintenance of physical, chemical, biological conditions	Soil formation and composition	Weathering, decomposition and fixing processes	**Soil formation**, expressed as N and P storage in the soil (ton.ha^{-1}.year^{-1})
		Atmospheric composition and climate regulation	Global climate regulation by reduction of greehouse gass concentrations	**Climate regulation**, expressed as organic carbon storage in soils and woody biomass (ton.ha^{-1}.year^{-1})
	Mediation of waste, toxics and other nuisances	Air quality regulation	Capturing fine dust, chemicals and smells	**Air quality regulation**, expressed as the amount of fine particulate matter (PM_{10}) captured by vegetation (kg.ha^{-1}.year^{-1})

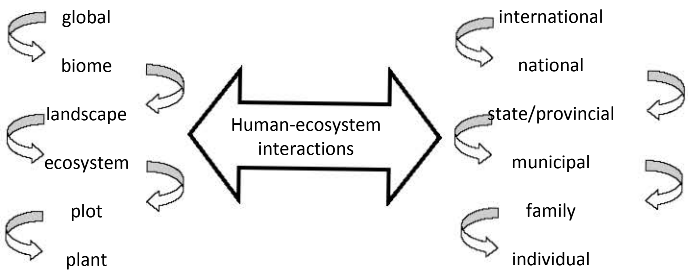


Figure 4.2: Mismatch between different ecological and institutional scales, which are important to model the supply of ecosystem services, and insititutional scales, which are important to model the demand side (Hein et al., 2006).

disadvantage will be discussed more in detail in the following chapter.

4.2.4 Model development

The initial aim was to develop a model structure that closely represented the functioning of the system, similar to mechanistic models. As discussed in chapter 2, the development of such model structures is generally based on expert knowledge. However, due to the inability to include feedback loops and lacking data to quantify all relations that are included by the experts, a more pragmatic approach was followed. Input variables were restricted to variables for which regional data were available and intermediate variables, and associated links, were only included in case supportive studies were found or in case equations or data were available that enabled quantification of these relations. This approach, however, may lead to neglecting potentially important processes. Nevertheless, when additional data or knowledge becomes available in the future, additional variables and relations can be easily added to the models. Although it may be possible to include variables and relations solely based on expert knowledge, this may reduce the credibility of the model. This is especially true for regional modelling of ES delivery as generally only a few qualified experts per service can be found. The final model structure is represented schematically in Figure 4.3. A graphical representation of the full model is included in appendix (Figure C.1).

Parametrisation of the regional models was based on a broad range of data sources, including, amongst others, datasets with a regional coverage, equations described in the literature, expert knowledge and key figures reported in technical reports. See Table C.1 for an overview of the consulted knowledge sources. The protocols used

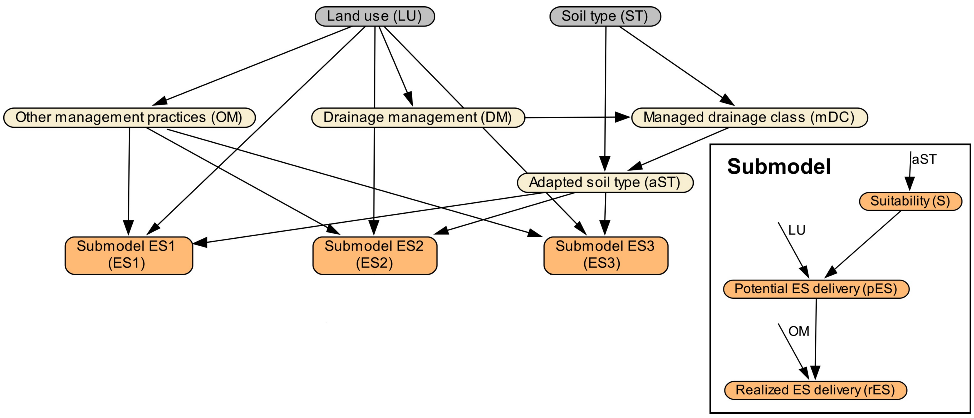


Figure 4.3: General framework to integrate the individual ecosystem service models.

to convert this knowledge and data into CPTs are listed in Appendix A.

4.2.5 Process description

Biophysical component

The set of input variables that are shared among all ES submodels are jointly referred to as the biophysical model component. This component describes the biophysical conditions of the system (or pixel), the management that is being carried out and the relations that exist among biophysical conditions mutually and among biophysical conditions and management practices. The considered biophysical conditions include soil texture, drainage class and profile development, which can all be derived from the soil map of Flanders (AGIV, 2001). On top, four variables describing actual and potential groundwater levels in summer and winter were included as well. Although only the actual groundwater level in winter was necessary to model the considered services, the other variables were included to improve the comprehensibility of the model as they clearly visualise the effect of drainage. Quantification of the relations between drainage class and ground water levels were based on data extracted from Stuurman et al. (2002). The considered management variables include land use and a set of specific management practices, such as, implementation of agro-environmental schemes, nature management and drainage management. Additionally, several input variables are included that describe the characteristics of the neighbourhood of a pixel. Distance to sewage infrastructure and permeability of the neighbourhood are two examples of such neighbourhood variables that were included in the model.

Dependencies among the model's input variables are an important aspect to consider during model development. Although defining such dependencies does not alter the model output in case all input variables are known or instantiated, it may have a significant effect when some of the input variables are left undefined during belief updating. As this is frequently the case during model exploration, dependencies among input variables definitely need to be taken into account. In this model, dependencies between land use and soil type were defined data-driven based on the soil map (AGIV, 2001) and the land use map (Poelmans and Van Daele, 2014) of Flanders. Similarly, relations between land use and distance to sewage infrastructure and between land use and distance to drainage ditches were defined.

Aside from quantifying conditional probabilities, also prior distributions of the model's input variables need to be defined. The prior distribution of the soil type variable was derived from the frequency distribution of soil types in Flanders (AGIV, 2001). The prior distribution of the land use variable was derived from the frequency distribution of land uses in Flanders (Poelmans and Van Daele, 2014).

Drainage management submodel

The presence of artificial drainage was modelled based on the difference between desired groundwater level (to maximise productivity), which depends on land use, and the natural groundwater level. On top, distance to streams and ditches that make artificial drainage possible was taken into account as well. A linear reduction of drainage efficiency was assumed between 100% and 0% for 0 and 500m respectively. Water level decreases were estimated by multiplying the desired water level decrease with drainage efficiency.

Drinking water production

The provision of potable water is approximated by the infiltration capacity of the landscape. The infiltration capacity or potential infiltration of the landscape depends on soil texture and groundwater depth (Batelaan and De Smedt, 2007). Soils with coarse texture and deep groundwater tables generally allow more infiltration compared to soils with clayey texture and a high groundwater table. Actual infiltration depends on potential infiltration and losses through evapotranspiration by vegetation or runoff from paved surfaces. Infiltration loss by evapotranspiration varies with vegetation type. In this study, recharge potential (based on soil texture and groundwater level) and vegetation-specific evapotranspiration percentages were quantified based on estimates provided by Batelaan and De Smedt (2007). As stated by (Batelaan and De Smedt, 2007), their estimates agree with measurements and model results obtained in several Belgian and Dutch studies on evapotranspiration and groundwater recharge. Infiltration loss due to runoff was assumed to occur only on paved surfaces according to findings from (Batelaan and De Smedt, 2007). To account for the presence of sewage infrastructure (loss through run-off is higher in case sewage infrastructure is present), distance to sewage infrastructure was included as a variable in the model. For low distances (0 m), a loss through run-off of 100% was assumed, while for high distances (higher than 100 m), a loss through run-off of 0% was assumed, with a linear decrease between both extremes. The combined effect of both mechanisms was expressed as a percentage loss of potential infiltration.

Wood production

Wood production depends on the biophysical suitability of the landscape and on land use and related management practices. Biophysical potential of the landscape was modelled based on a suitability scoring approach, carried out for all frequently occurring tree species in Flanders (De Vos, 2000). These suitability scores were used to derive expected productivity rates ($m^3.ha^{-1}.year^{-1}$) for each tree species. Species-specific productivity rates, dependent on soil suitability, were determined based on existing literature and field studies on forest productivity (Moonen et al., 2011; Jansen et al., 1996). To account for the effect of management, harvest factors were used to differentiate between state-owned forests and private forests. The harvest factors were derived from recent data on timber selling (2009-2012) and were set to 0.15 and 0.54 for private and state-owned forest, respectively (Broekx et al., 2013a). As these harvest factors are slightly lower than those estimated by Kint (2013), harvest volumes might be underestimated. Based on species-specific market prices, derived from a statistical analysis on a database of actual selling prices in Flanders (Demey et al., 2013), harvest amounts were converted into monetary values ($€.ha^{-1}.year^{-1}$). Although Demey et al. (2013) took into account stem circumference as a predictor for wood price, this factor was not included in the model. Stem circumference of harvested wood is hard to predict on a regional scale as no detailed spatial data on forest management types are available. To account for differences in prices due to differences in wood circumference, for each wood species a weighted average price was calculated based on the circumference-specific prices and the frequency distribution of circumference classes that were present in the database. As uncertainties associated to suitability scores and production rates were not reported,

Table 4.2: Link between soil suitability and yield loss, expressed as a percentage of potential yield.

Soil suitability	1	2	3	4	5
Yield loss(%)	0	10	25	45	70

all CPTs were populated deterministically.

Agricultural production

Food production depends on the biophysical suitability of the land and on land use, a combination of land cover (choice of crop type) and land management. Biophysical suitability for agriculture mainly depends on the soil characteristics mapped in the soil map of Flanders: soil texture, drainage class and profile development. For each combination of these soil characteristics, a suitability score has been determined (1: highly suitable to 5: unsuitable) (Bollen, 2012). Each suitability class represents a different yield loss, expressed as a percentage of potential yield.

Data on actual yield were derived from Van Broekhoven et al. (2012). Based on the bookkeepings of 749 farms in Flanders, they provide data on the net benefit (€.ha^{-1}.year^{-1}) obtained by performing different agricultural activities. The document reports for each agricultural activity the 25th percentile, the mean and the 75th percentile of the recorded net income data. By fitting a normal distribution to these percentiles a probability distribution for the net benefit generated by each activity was obtained. This probability distribution for a specific agricultural activity is, however, a combined result of the suitability of the Flemish soils used for that activity and the potential yield that can be obtained with that agricultural activity. To disentangle both aspects, the net benefit (being a probability distribution) for each agricultural activity was divided by the average production efficiency of the Flemish soils used for that activity (production efficiency = one minus the expected yield loss). This average production efficiency was obtained through an overlay of land use data and soil suitability data. The obtained probability distribution, hence, represents the maximum net benefit that can be obtained through a specific agricultural activity and was used to populate the CPTs of the potential yield node in the model. Subsequently, the actual yield for a pixel was calculated by multiplying the potential yield with the pixel's production efficiency derived from the soil characteristics of that pixel. An important shortcoming of this approach is that the monetary values are not corrected for subsidies. For some crops, this correction would lead to a decrease of the net income of around 80%. Hence, the applied method overestimates the monetary value of food production from a social perspective.

Climate regulation

The capacity of an ecosystem to regulate the climate is to a large extent determined by its capacity to store organic carbon, both in above and below ground biomass and in the soil. As only carbon storage in the soil and in woody biomass can be seen as a semi-permanent storage, only these types of organic carbon storage were considered. To model soil organic carbon (SOC) storage, the available literature was used as a basis. Although many mechanistic SOC models have been developed in the past (Skjemstad et al., 2004; Byun and Schere, 2006), their extensive data requirements makes them only applicable in small, field scale studies. To obtain a regionally applicable model, an empirical study on SOC storage conducted in Flanders was used (Meersmans et al., 2008). Although more recent studies are available (e.g. Ottoy et al., 2015), the level of detail studied by Meersmans et al. (2008) matched the desired level of detail of the BBN. In the study of Meersmans et al. (2008), a regression model has been developed which predicts SOC storage based on soil texture, soil moisture content and land use (grassland, heathland, cropland and forest). The graphical network of the BBN was structured accordingly. The regression model's SOC estimates for each combination of soil texture, soil moisture content and land use were used to populate the CPTs of the BBN. As confidence intervals were available for each estimate, uncertainties could be taken into account in the model's CPTs. For grasslands, a correction factor was included to account for differences between SOC storage in permanent and temporary grasslands based on findings from Van Cleemput et al. (2007). As the outcome of the regression formula must be interpreted as an estimate of the equilibrium SOC stock, the obtained values were divided by 100 to approximate yearly SOC gains, assuming that soils reach their equilibrium SOC concentration after a period of 100 years. Although it is known that the length of this period is highly variable (from 10 to more than 200 years) (Kirschbaum et al., 2001; Kim and Kirschbaum, 2015), a period of 100 years was used as a save estimate to avoid potential overestimations. Carbon storage in woody biomass was modelled based on the wood production submodel. Productivity rates were converted into yearly carbon gains using species-specific biomass expansion factors (to estimate above and below ground biomass based on stem volume) and carbon density values reported by Van de Walle et al. (2005). To obtain an estimate of yearly total carbon storage, yearly carbon storage in biomass and yearly carbon storage in soils were summed.

Air quality regulation

The concentration of particulate matter, and more specifically PM_{10}, accounts for the majority of the impacts of air pollution on human health in Flanders (MIRA-T, 2009). Therefore, PM_{10} capture was chosen as proxy for air quality regulation. The impact of vegetation on other pollutants such as sulphur dioxide, nitrogen dioxide and ozone was not considered. Natural vegetation and forests are known to capture large amounts of air pollutants such as PM_{10}. Modelling the concentration of PM_{10} and the amount that is captured by the vegetation is complex and depends on numerous local conditions, such as, PM_{10} concentration in the air, wind speed, the total amount of leaf area, roughness of the vegetation and plant species (Schaubroeck et al., 2014; Nowak et al., 2013; Sæ bøet al., 2012). However, to be able to integrate this service into a BBN that is applicable on a regional scale, estimates of particulate matter capture per unit area of several broad vegetation classes were used. The applied estimates, gathered through a review of the literature, are reported in Table 4.3. As for each vegetation type minimum and maximum estimates were found, uniform distributions between the minimum and the maximum estimate were used to populate the CPTs that quantify the causal link between land use and PM_{10} capture. The values reported in Table 4.3 deviate from those recently modelled for a pine forest in Flanders (Schaubroeck et al., 2014). This deviation can be attributed to the applied definition of particulate matter ($PM_{2.5}$ in the study of Schaubroeck et al. (2014) versus PM_{10} in this study) and whether resuspension effects, that may substantially lower the net PM capture by vegetation, are taken into account. Schaubroeck et al. (2014) and Nowak et al. (2013) report resuspension percentages for forests of 76% and 34% , respectively. This high variability of reported resuspension percentages and the absence of estimates for other vegetation types impeded the inclusion of this process in the model. Thus, the presented values probably overestimate air quality regulation by vegetation.

Soil formation

The capacity of the soil to store N and P can be regarded both as a regulating service and a supporting service. In case a change in the ecosystem causes the N and P concentrations in the soil to lower, this can be regarded as a cost as it increases the cost of water treatment due to increased nutrient leaching to the water. In case a

Table 4.3: Minimum and maximum values for PM_{10} capture by different vegetation types (based on: Tiwary et al. (2009); Nowak et al. (2006); Oosterbaan et al. (2006); Melman and van der Heide (2011)).

Vegetation type	PM_{10} capture (kg.ha^{-1})
Grassland	18-36
Cropland	6.4-12
Broadleaf forest	36-88
Coniferous forest	63-126

Table 4.4: C/N ratios for different vegetation types (adapted from Liekens et al. (2013b)).

Vegetation type	C/N ratio
Cropland and productive grassland	8-12
Grassland (nature management)	10-14
Broadleaf forest	15-25
Mixed forest	20-25
Coniferous forest	25-30
Heathland	25-35
Wetland	25-35

shift results in an increase of N and P, this cannot always be regarded as a benefit in terms of reducing the cost of water treatment. In some cases an increase of N and P concentration does not substitute nutrient leaching in case no changes occur. In these situations an increase of N and P contributes, for example, to an increased suitability of the soil for food production, a benefit that is generally referred to as the ES soil formation. Due to this ambiguity, the valuation step is omitted in the current model and N and P storage (kg.ha^{-1}.year^{-1}) is considered as the endpoint that is being modelled in the analysis. In the model, N and P storage is estimated based on the capacity of the soil to store organic carbon. By using reported C/N ratios for different vegetation types (Table 4.4), soil organic carbon storage can be linked to N storage. To derive P storage, a fixed N/P ratio of 15 is used, according to findings from Koerselman and Meuleman (2015). Similar N/P ratios have been reported by Cleveland and Liptzin (2007).

4.2.6 Analysis of model results

Sensitivity analysis

To test the regional model and to identify the importance of individual nodes, a sensitivity analysis of the model is carried out (see section 3.2.6 for more detailed information on sensitivity analysis of BBNs). The sensitivity analysis can be used both to check whether the model's sensitivities accord with reality and to identify

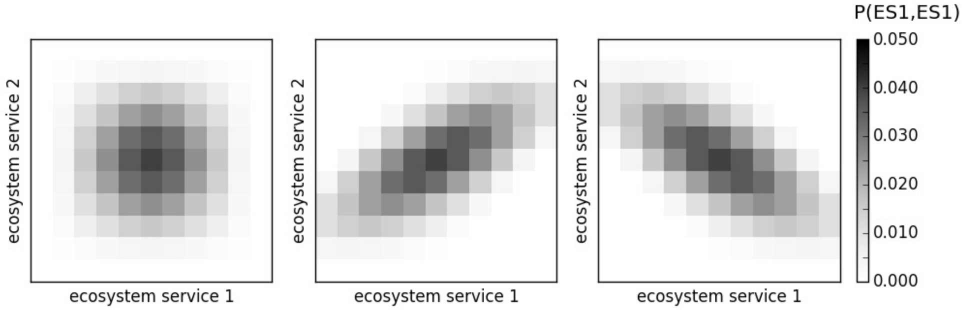


Figure 4.4: Joint probability distributions for two services with a symmetric, marginal probability distribution, denoting an independency (left), a synergy (middle) or a trade-off (right) among both services. Top right pixels represent the joint probability of a high delivery of both services, bottom left pixels denote the joint probability of a low delivery of both services.

those variables that influence ES delivery the most. The results of a sensitivity analysis, however, need to be interpreted with caution. The results do not necessarily reflect reality, but rather patterns that emerge from the integration of different knowledge sources. In other words, the outcome needs to be interpreted conditional on the data that was inserted.

Analysing interactions among services

While BBNs are generally used to predict probability distributions of individual nodes, they can also be used to calculate the joint probability distribution of a pair of nodes (Equation 4.1). These joint probability distributions, calculated for two services, can provide insights into synergies or trade-offs among them. As an illustration, the joint probability distribution for three types of interactions are represented in figure 4.4.

$$P(ES_1, ES_2) = P(ES_1|ES_2) * P(ES_2) \tag{4.1}$$

In case ecosystem functions are included as variables in the model, interactions can be studied on the level of these variables as well. As synergies and trade-offs often occur in specific situations, joint probability distributions can also be calculated conditional on these situations (Equation 4.2). This enables, for example, analysing whether synergies and trade-offs among services differ for different biophysical conditions.

$$P(ES_1, ES_2|C) = P(ES_1|ES_2, C) * P(ES_2|C)) \tag{4.2}$$

Based on these joint probability distributions, frequently applied interaction indicators, such as, covariance and correlation coefficients can be calculated (Equation 4.3 and 4.4).

$$Covariance = \sum_{i=1}^{n}\sum_{j=1}^{m} P(ES_1 = S_i, ES_2 = S_j) * (S_i - E[ES_1])(S_j - E[ES_2]) \tag{4.3}$$

$$Correlation = \frac{Covariance}{\sigma(ES_1) * \sigma(ES_2)} \tag{4.4}$$

4.3 Results

4.3.1 Regional ecosystem service delivery

Figure 4.5 represents the model's predictions for two agricultural and two semi-natural land uses: cropland, grassland, forest and heathland. The distributions presented in this figure can be interpreted as posterior probability distributions of ES delivery in Flanders given a particular land use class. The flatness of some of the bar plots indicates that ES delivery is highly uncertain for that specific land use (e.g. drinking water production of cropland). However, the uncertainty of the model's predictions will likely decrease in case soil type and management practices are specified as well. Some distributions are highly skewed. The lowest strictly positive state has a high probability of occurring, while this probability rapidly decreases for higher states (see, for example, the predictions for soil formation and climate regulation). This skewness denotes that high delivery rates are possible, but only occur under relatively rare biophysical conditions and under infrequently applied management practices. Service production by forests is the most balanced with a strictly positive delivery for all services aside from food production. Figure 4.5 shows that heathland are associated to low delivery rates for most studied services. Only drinking water production is slightly higher compared to the other land uses. Although the low variability among the posterior distributions for drinking water production suggest that the effect of land use on the delivery of this service is minimal, lower evapotranspiration rates of heathland vegetation may explain the slightly higher delivery by heathland. An indirect cause may be the association between heathland and dry sandy soils that promote infiltration.

4.3.2 Sensitivity analysis

Figure 4.6 graphically represents the output of the sensitivity analyses, carried out for each ES delivery node in the model. For each ES delivery node, high variance reduction values (dark-coloured cells) were found for several nodes belonging to the land use submodel and, logically, for nodes belonging to their own submodel. All nodes belonging to the soil type submodel expose low variance reduction values for all services, except for drinking water production. In other words, for most services the decrease in uncertainty of predicted ES delivery due to information on land use is significantly larger compared to the decrease in uncertainty due to information on soil type. However, soil type might have the potential to lower the uncertainty further within ES delivery predictions for specific land uses (see below). A lot of similarities can be observed between the sensitivity analyses of the air quality regulation node, the climate regulation node and the wood production node. This denotes that the production processes of these services are highly related. These interactions are probably all driven by the presence or absence of forests. The sensitivity analyses of the soil formation node and the drinking water production node also show some similarities. The drainage class of the soil and variables related to drainage management are clearly more important for these services (higher sensitivity values). This finding points at the importance of soil moisture content as a driving force for the delivery of these services.

To investigate the influence of soil type on ES delivery more in depth, additional sensitivity analyses were carried out. Findings for several land uses were inserted into the model to investigate the influence of soil type on the model's predictions for those specific land uses. The bar plots in Figure 4.7 represent the obtained relative variance reduction values for three variables that determine soil type: soil texture, drainage class and profile development. The potential of soil type to reduce the variance of the model's predictions clearly depends on the service being modelled and the considered land use. For all land uses, drainage class seems to be the most determining variable, especially for drinking water production. The influence of soil type on ES delivery seems to differ between croplands and grasslands. ES delivery by grasslands is influenced the most by soil type. In general, ES delivery by forests and grasslands seems to be influenced the most by soil type.

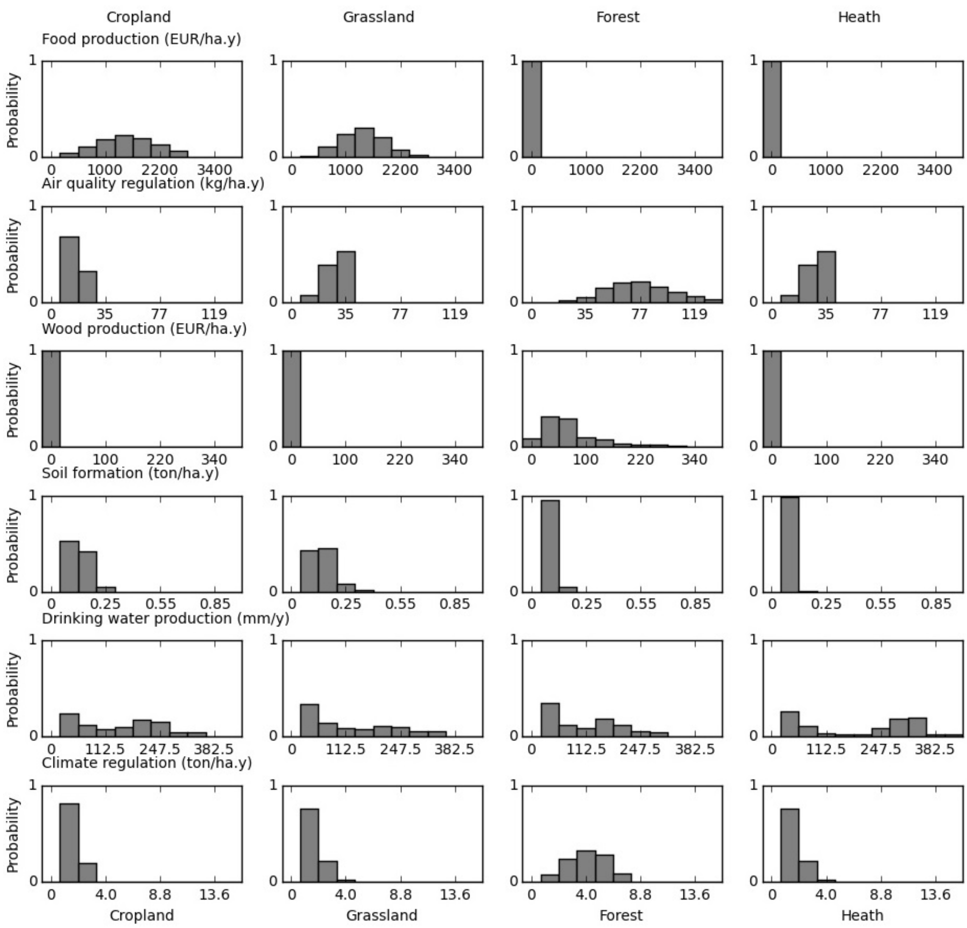


Figure 4.5: Predicted ecosystem service delivery in Flanders for different land uses, expressed as a posterior probability distribution P(ecosystem service delivery|land use).

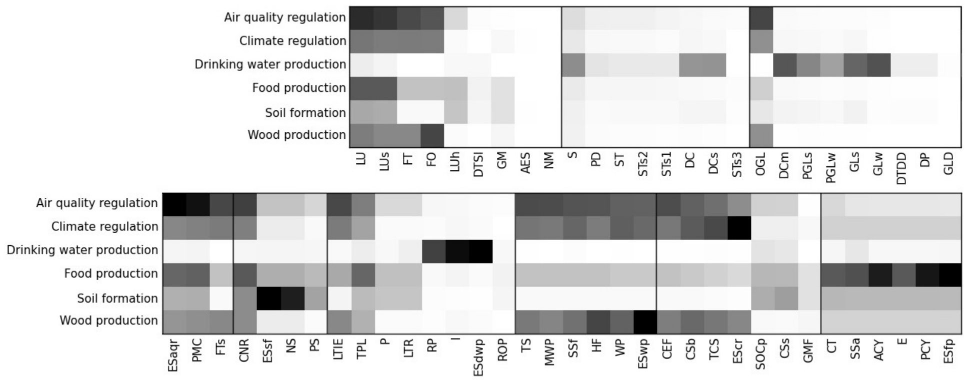


Figure 4.6: The sensitivity of the ecosystem service delivery nodes to findings in other nodes of the network. High sensitivity values (a variance reduction percentage close to 100%) are represented by dark-coloured cells, while low values are represented by light-coloured cells. Sensitivities to findings in the nodes of the submodels on land use, soil type and drainage management are shown at the top, sensitivities to findings in the nodes of the ecosystem service submodels are shown at the bottom. A reference to the full names of the model's variables is provided in Table C.1.

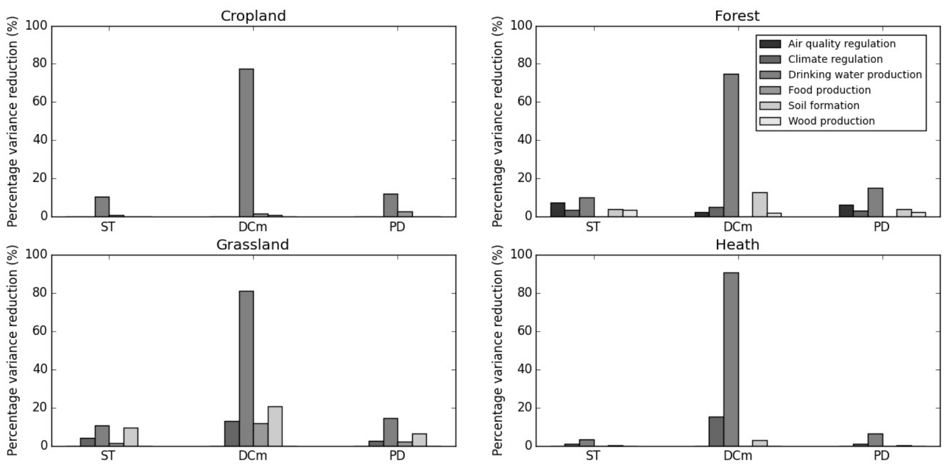


Figure 4.7: The sensitivity of the ecosystem service delivery nodes to findings in the nodes that depict soil type in case land use is known. The considered soil type related variables include soil texture (ST), drainage class (DCm) and profile development (PD).

4.3.3 Interactions among service

Figure 4.8a represents interactions among services as joint probability distributions for all possible pairs of services. The correlation coefficients, calculated for each joint probability distribution, are provided at the other side of the diagonal. Although the calculated correlation coefficients point at moderate to high correlations among the production rates of some services, none of these interactions are clearly visible in the provided joint probability distributions. Skewness of the services' marginal probability distributions and unequal variances may hinder proper interpretation of the joint probability distributions. However, some apparent patterns can be distinguished. Sharp L-shaped probability distributions denote services that exclude each other (e.g. wood production and food production), while more or less uniformly coloured images and circular patterns point at correlation coefficients close to zero (e.g. food production and drinking water production). Moderate to high positive correlations were found for several service pairs: wood production and air quality regulation (0.56), wood production and climate regulation (0.65), air quality regulation and climate regulation (0.64) and soil formation and food production (0.44). Negative correlations were found between food production, at the one hand, and climate regulation (-0.37), wood production (-0.34) and air quality regulation (-0.26), at the other hand.

Most of the identified positive correlations seems to be linked to the presence of forests. Forests are effective in capturing fine particulate matter, produce wood and store carbon in biomass. Recalculation of the interactions, for forests only, confirms this hypothesis (Figure 4.8b). Correlation coefficients that were previously high, drop to zero when only forests are considered. This suggests that within forests a higher delivery of one service does not necessarily results in a higher delivery of the other service. Only the correlation between wood production and climate regulation remains positive. Higher wood production rates logically cause higher carbon storage rates in woody biomass.

4.4 Discussion

4.4.1 Bayesian belief networks to model regional ecosystem service delivery

The developed BBN model for ES assessment at the regional scale exhibits some important advantages over existing methods to model ES delivery in Flanders. Aside

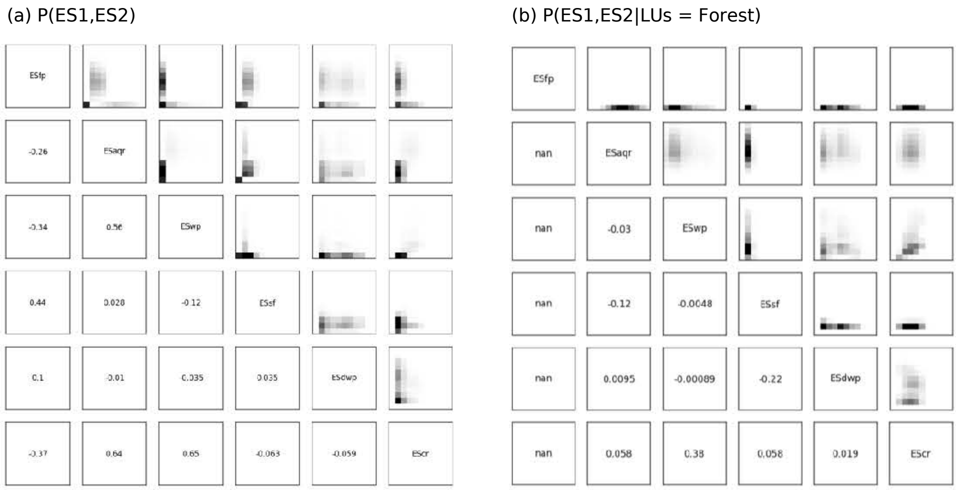


Figure 4.8: Interactions among ecosystem services represented as joint probability distributions and correlation coefficients (ESfp = food production, ESaqr = air quality regulation, ESwp = wood production, ESsf = soil formation, ESdwp = drinking water production, EScr = climate regulation). The discrete joint probability distributions are represented by raster images with dark-coloured cells for high probability values and light-coloured cells for low probability values. The values in the panels represent correlation coefficients, calculated based on the joint probability distributions. Joint probability distributions are first calculated without findings inserted into the model (a) and given that the land use is forest (b).

from being renowned for its ability to account for uncertainties, BBN modelling offers a standardised approach to integrate existing knowledge and models in Flanders. Moreover, its graphical nature makes that existing knowledge and data are integrated transparently and that a review of the model by external experts can be carried out easily (e.g. Ticehurst et al., 2007). Similarly, assumptions, that are frequently integrated in ES models to deal with unknown processes, can be evaluated easily. Aguilera et al. (2011) identified expert-based validation as one of the most popular validation approaches to validate BBNs in the environmental sciences and ecology research domain. Aside from being an operational model that can be used for predictions (chapter 5) and forecasting (chapter 6), the developed model can be seen as a graphical database that contains most of the available knowledge on the delivery processes of the studied services. Next to the names of the states, the applied discretisation, a CPT and an equation, additional information can be attached to the nodes of the network depending on the software that is being used to develop the model. In this study, content that was included to enhance the model's informativeness include links to publications and reports, references to key figures and statements about assumptions. The developed model can, thus, be seen both as an operational model and as an informative database of information related to ES delivery in Flanders.

An important drawback of the proposed model is its linear nature which impedes that all services that are relevant within the Flemish context can be modelled. Recreational use, a very important service in Flanders, is, for example, a service were feedbacks might play a crucial role in its production process. An ecosystem can, for example, attract that much visitors that, when above a certain threshold, crowdedness may have a repulsive effect (e.g. Hammitt and Patterson, 1991; Anderson and Brown, 1984; Vaske et al., 1980). This repulsive effect can be seen as a feedback that lowers the amount of visitors that are attracted. Similar feedbacks often occur among the delivery processes of different services. Intensive abstraction of drinking water can, for example, alter the moisture content of the soil which will, in turn, alter soil organic carbon sequestration rates. However, as already pointed out in chapter 2, workarounds exist. Feedbacks can be integrated in a BBN by duplicating the model for several time steps and by specifying feedbacks as causal relations among the nodes of models that represent successive time steps (e.g. Johnson et al., 2010). Nevertheless, it should be noted that although being important, only very few ES studies have ever accounted for these feedbacks (Boumans et al., 2002). Also the most complex models included in InVEST, for example, do not account for feedbacks (Seppelt et al., 2011).

4.4.2 Drivers that determine ecosystem service delivery in Flanders

The sensitivity analysis of the model clearly points at land use as one of most important drivers that determine ES delivery. This finding suggests that the focus on land use in many ES-related studies in the past (e.g. Burkhard et al., 2009; Schneiders et al., 2012) was justified. Considering extra input variables, such as soil characteristics, has only a small added value as it lowers the uncertainty of the model's predictions only slightly (relative variance reduction values lower than 10% for most services). These findings, however, need to be treated with caution. As the model was developed based on information collected from reports and scientific publications and not based on raw data on land use, soil characteristics and ES delivery, the importance of land use may as well be a result of the higher number of studies that have investigated the effect of land use and, thus, the higher amount of land use-related relations integrated into the model. Hence, this study is not a proof of the importance of land use, rather a proof that based on current knowledge land use based assessments are justified. Nevertheless, it is important that the effect of other variables, such as, soil type, keeps on being studied so that this information, if valuable, can be integrated into models in the future.

On the other hand, it needs to be mentioned that the explanatory power of land use for modelling drinking water production was considerably lower. This suggests that for some services focussing on land use only is not justified. This finding confirms the study of Van der Biest et al. (2015), who point at the importance of the abiotic environment, especially for regulating services. They argue that land use-based assessment may work in case land use is in accordance with its abiotic environment, or in other words, that for a specific land use soil type does not vary a lot. This assumption, however, is not true for Flanders where land is scarce and suboptimal soils are being used as well.

Although a consensus exists that selection of proper input variables is important for modelling ES delivery (Grêt-Regamey et al., 2014), less effort have been invested in analysing the explanatory power of different input variables. In contrast to existing approaches to analyse the importance of different drivers, BBN modelling offers a more objective approach. Instead of comparing different model types to analyse the importance of different drivers (Van der Biest et al., 2015), driver importance can be readily assessed within one BBN model.

4.4.3 Trade-offs and synergies among ecosystem services

The obtained correlation coefficients suggest that several trade-offs and synergies among the studied services exist. Two clear service bundles could be identified: one bundle as a result of synergies among the services wood production, climate regulation and air quality regulation, and one bundle as a result of synergies among the services food production and soil formation. High synergies between wood production and regulating services was also identified by Schneiders et al. (2012). Disappearance of most of these interactions in case land use is known reveals that land use is one of the main drivers that determine the occurence of these bundles.

The use of BBNs and joint probability distributions instead of pairwise comparison of ES maps to identify interactions among services has a couple of advantages, especially in case no primary data on ES delivery is available. In this situation, interactions are often studied by means of comparing pairs of land use-based ES delivery maps. By using BBNs to identify interactions the mapping step can be skipped. Secondly, because maps easily require several gigabytes of memory, there's a difference in resource usage. Memory usage of a BBN will be considerably lower compared to that of a set of maps. The model presented in this chapter, for example, only requires less than 200 kilobytes. A final advantage of the proposed approach is that not only interactions can be quantified, but also drivers that affect these interactions can be identified. Bennett et al. (2009) mentioned this as one of the shortcomings of most studies that investigate interactions. Knowledge on trade-offs and synergies is worthless in case nothing is known about the processes that drive these interactions as management can only support synergies or mitigate trade-offs in case the drivers to react upon are known. In case primary data on ES delivery is available, multivariate statistical approaches, such as, ANOVA, MANOVA, ordination methods (e.g. Hicks et al., 2013; Martín-López et al., 2012) are probably more suitable compared to BBNs to identify interactions among services (Mouchet et al., 2014).

A limitation of the proposed approach is that the identified interactions are a direct result of the information that has been put into the model. Integrating additional processes in case new information becomes available can alter the identified interactions. For example, while a trade-off is expected between food production and drinking water production due to fertiliser use, it could not be identified as only water quantity and not quality was considered to model drinking water production.

Therefore, models need to be developed as complete as possible. In case no data is available for several relationships, expert knowledge can be an alternative.

4.5 Conclusion and recommendations

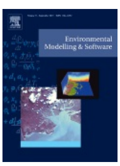
As illustrated in this chapter, BBNs offer an interesting approach to integrate knowledge on ES delivery at the regional level. The obtained models can be used for several purposes: to make predictions taking into account uncertainties, to gain system understanding through model exploration and as a visual library that contains information on the delivery processes of several services and the interactions among them. Interactions among services can be explored through joint probability distributions, an approach that is more efficient compared to pairwise comparison of ES delivery maps.

The results of model explorations, however, need to be treated with caution as they completely depend on the knowledge that is inserted into the model. Missing variables, relationships, land use classes or management practices may alter the identified interactions or the results of a sensitivity analysis. Therefore, models need to be as complete as possible, for example, by including expert knowledge in case no data are available. Nevertheless, unexpected outcomes of sensitivity analyses and interaction analyses can be a valuable input for model evaluation processes as they may suggest the presence of flaws in the model.

5 A software framework to account for uncertainties in ecosystem service mapping

One of the advantages of the regional model, described in the previous chapter, is the ability to take into account uncertainties. The added value of this feature for decision making has been discussed in chapter 2. Uncertainties attached to the output of the model affected the way differences between alternative pond management practices were evaluated. Although these uncertainties may also be important for decision-making at the regional level, regional ecosystem service assessment and mapping approaches do generally not account for uncertainties. At the regional level, predictions of ecosystem service models are generally represented spatially. To make optimal use of information on uncertainties that is provided by a Bayesian belief network model, ways need to be found to represent uncertainties on maps and to match these uncertainty representations to decision makers demands. As a first step towards this aim, a transparent coupling between Bayesian belief network and GIS software was set up. This chapter subsequently discusses the developed software framework, different ways to represent uncertainties on maps and how these different representations may respond to different problems decision makers are confronted with.

This chapter is based on:



Landuyt, D., Van der Biest, K., Broekx, S., et al., 2015. A GIS plug-in for Bayesian belief networks: Towards a transparent framework to assess and visualise uncertainties in ecosystem service modelling. Environmental Modelling and Sofware 71, 30-38.

5.1 Mapping uncertainties in ecosystem service assessments: the state-of-the-art

Primary data on ES delivery, and especially primary data with a regional coverage, is generally absent. As discussed in detail in chapter 1, this has led to the development of a broad range of models to obtain regional estimates of ES delivery. Although model predictions are usually uncertain (Hou et al., 2013), in the past, only a subset of ES modelling studies have taken uncertainties into account and only one-third of these studies accounted for uncertainties quantitatively (Seppelt et al., 2011). Uncertainty in model outputs arises from the uncertainty associated with predicting the outcome of natural processes that drive ES supply (natural supply uncertainty), from the uncertainty associated with people's preferences and demands for ES (preference uncertainty) and from the uncertainty associated to the applied modelling tool (Hou et al., 2013). A reason for the low amount of studies that have taken uncertainties into account might be that accounting for uncertainties in complex GIS models is challenging. These frequently applied modelling techniques in ES studies require an uncertainty analysis posterior to model development (Jakeman et al., 2006), while for most statistical models uncertainty analyses are integrated into the model development procedures (Smith et al., 2011).

Also spatial representation of modelled uncertainties has not been very popular in ES modelling studies. To illustrate this, in two recent reviews of ES mapping studies, uncertainty has not been mentioned once (Nemec and Raudsepp-Hearne, 2013; Martínez-Harms and Balvanera, 2012). The review of studies that used BBNs to model ES delivery, presented in chapter 2, also shows that mapping uncertainties is not always carried out, although BBN models readily deliver information related to uncertainties. Only one-third of the reviewed studies apply their models spatially and provide maps with information on uncertainty (e.g. Smith et al., 2007; Haines-Young, 2011). However, no efforts have been made to represent uncertainties in a way that is meaningful for decision makers. While several studies have been conducted on visualising uncertainties on maps (MacEachren et al., 2005), mapping methodologies in BNN-based ES modelling research are still restricted to mapping either the most probable state (e.g. Lehmkuhl et al., 2001; Haines-Young, 2011; Raphael et al., 2001) or the probability of one particular state (Smith et al., 2007; Rieman et al., 2001) of the network's output node.

In this chapter, a software framework is proposed which couples BBN software, to model ES delivery processes, and geographical information software, to map ES delivery and associated uncertainties. Netica (Norsys Software Corporation, 1998), a software package that is frequently used in ES modelling research (chapter 2) and that was also applied for all model development and analysis tasks during this thesis, was selected as model development platform due to its user-friendly interface. Quantum GIS (QGIS) (QGIS Development Team, 2012), freely available geographical information software, was chosen as interface to visualise and to process input and output maps. The framework - a plug-in for QGIS - is developed in such a way that it is not restricted to ES mapping applications, but can be used in a broad range of research domains that are confronted with spatial processes and uncertainties. Researchers with different backgrounds should be able to apply the plug-in. The main functionalities of the plug-in are illustrated by applying the regional ES delivery model, described in the previous chapter, on spatial data of a land dune region, located in the northern part of Belgium. Several approaches to convey probabilistic uncertainties on maps are illustrated and their applicability in decision support is discussed.

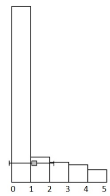
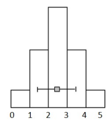
5.2 Methods

5.2.1 Mapping Bayesian belief network predictions

The model described in the previous chapter focusses on pixel-based ES delivery. The application of the model for mapping will also be on the level of individual pixels. Pixel characteristics are used as model input and will instantiate the input nodes of the network. After the inserted information is propagated through the network, the network returns a probabilistic estimate for its output variable which can be assigned to the pixel again.

An important advantage of using BBNs in spatial analyses is the ability to deal with missing data. For some pixels in the study area one or more characteristics may be unknown, resulting in uninstantiated input nodes in the network. In this case, a BBN model is able to make a prediction for that pixel, albeit more uncertain, based on the input variables' prior distributions. These prior distributions can be estimated based on the characteristics of the entire study area. The predicted distributions presented in Figure 4.5 of the previous chapter illustrate this feature. Predictions could be made for different land uses without having information on the texture of the soil, its moisture content and so one. These predictions, however, are more uncertain

Table 5.1: An overview of indicators that can be derived from the probability distribution of a Bayesian belief network's output node. Real value examples for a highly skewed and an unskewed discrete probability distribution are provided. S represents the output variable's set of states.

			
Terminology	**Equation**	**Skewed distribution**	**Unskewed distribution**
Most probable state	$MPS[X] = \arg\max_{x \in S} P(x)$	0.5	2.5
Probability of the most probable state	$PMPS[X] = \max_{x \in S} P(x)$	70%	40%
Expected value	$E[X] = \sum_{x \in S} P(x) * x$	1.17	2.5
Standard deviation	$SD[X] = \sqrt{\sum_{x \in S} (E[X] - x)^2 * P(x)}$	1.18	1.01
Cumulative probability	$P(X > T) = \sum_{x > T} P(x)$	20% (for T = 2)	70% (for T = 2)

than predictions obtained through running the model based on information on land use and soil type.

Table 5.1 presents several indicators that can be used to map the probabilistic output of a BBN: the expected value, the most probable state (or mode), the standard deviation of the expected value and the probability of the most probable state. The two first indicators are used to produce maps that represent quantity (hereafter referred to as quantity maps) while the other two are used to produce maps that represent the uncertainty associated to that quantity (hereafter referred to as uncertainty maps). Both map types deliver important information to support decision making (e.g. Ligmann-Zielinska and Jankowski, 2014). Additionally, three more advanced output maps are proposed that combine information on uncertainty and quantity in a single layer: ignorance maps, sampled maps and cumulative probability maps. Ignorance maps represent for each pixel the most probable state only in case the probability of attaining that state is higher than a predefined threshold (Rocchini et al., 2011). Map samples represent for each pixel a sampled state, sampled out of the output node's probability distribution. Cumulative probability maps represent for each pixel the probability that the model's prediction is higher than a predefined threshold.

5.2.2 Plug-in architecture

The software framework is designed to enhance interaction between BBN models and spatial data. It integrates the graphical user interfaces for BBN model development (Netica) and spatial data visualisation (QGIS) through a QGIS plug-in written in Python (van Rossum, 1995). After the user feeds in a BBN model and a set of spatial datasets for all input variables of the developed model, the plug-in will return several maps representing different types of BBN model output. The plug-in performs four main tasks. It preprocesses the spatial input data (1), merges the raster datasets into one joint input database (2), runs the model for each line of this database (3) and maps different types of BBN model output (4).

Figure 5.1 schematically represents the architecture of the framework. For each input node of the developed BBN, a raster layer should be available. As input raster data, the plug-in accepts GeoTIFF (.tif) files. As these files only support numerical data, each raster input file should be accompanied with a .csv file which assigns to each mapped, numerical code a name referring to a particular state of the corresponding input node. The pre-processing of the input rasters is automatically done by the plug-in and consists of excluding non-overlapping areas and eliminating raster offset.

After reshaping, all input rasters are merged into one joint map database (.csv format). The plug-in offers two possible ways to run the model. A fast run which requires considerable amounts of memory or a slow run with less memory usage. The slow run mode is based on a built-in function of Netica and runs the BBN model for each pixel (or row of the joint map database) independently. In the fast run mode, only unique pixels are retrieved from the joint map database and the model is run on this substantially smaller set of pixels. The output of this model run is used to generate a look-up table that lists all unique pixels with their corresponding probabilistic model output. This table, implemented as a dictionary structure in Python, is then used to assign a model output to each pixel of the study area. As dictionary structures allocate considerable amounts of memory, large numbers of unique pixels may cause memory errors. Using the fast run mode in combination with networks that require a large set of input maps is therefore not recommended. After running the model, raster output files are produced. The dialog screen of the plug-in (Figure 5.2) offers the possibility to select one or more output maps. The user can select among seven types of BBN output maps, previously discussed in section 5.2.1.

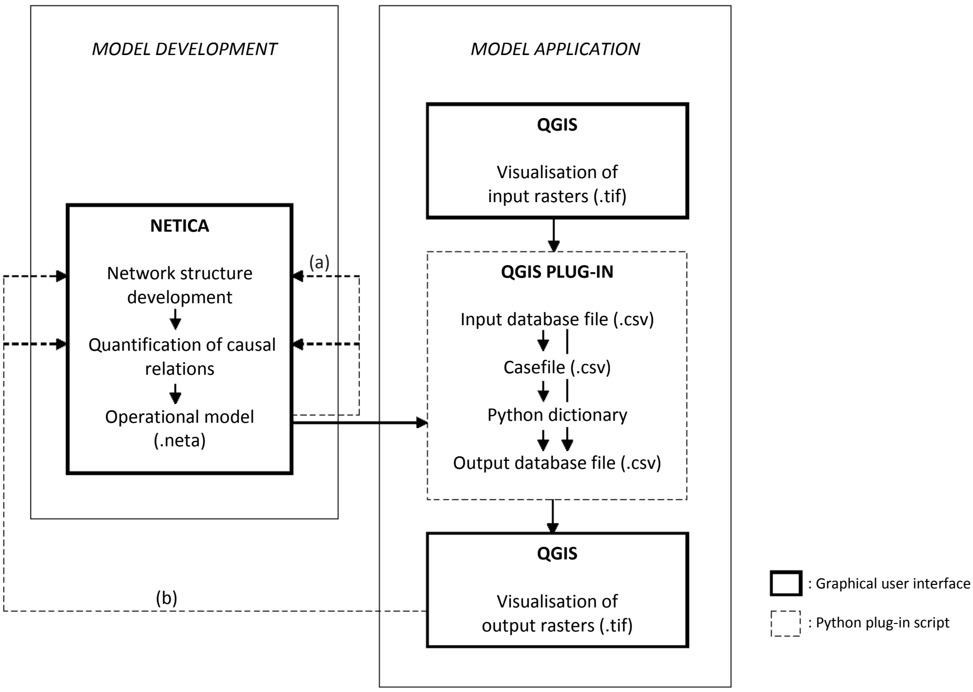


Figure 5.1: Schematic visualisation of the plug-in architecture, embedded in an adaptive model development framework. Full arrows represent conventional plug-in usage: a Bayesian belief network model is developed in Netica (left) and subsequently applied on spatial raster data by using the plug-in (right). Feedback loops (a) and (b) represent potential adaptive model development pathways, using respectively non-spatial and spatial model output to revise the previously developed model.

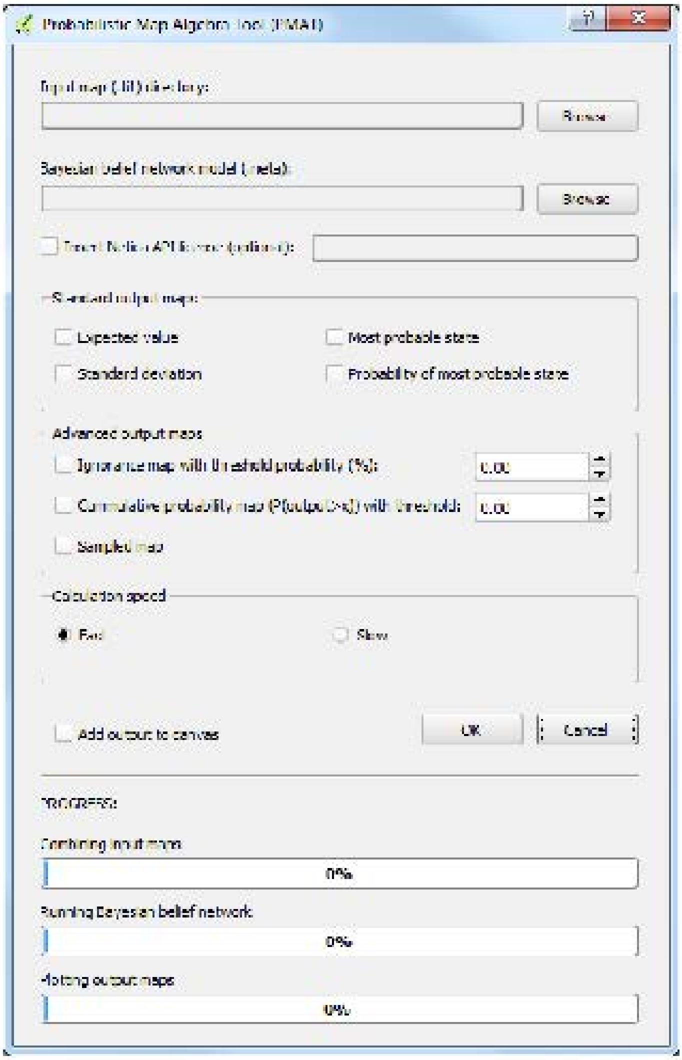


Figure 5.2: Dialog screen of the QGIS plug-in.

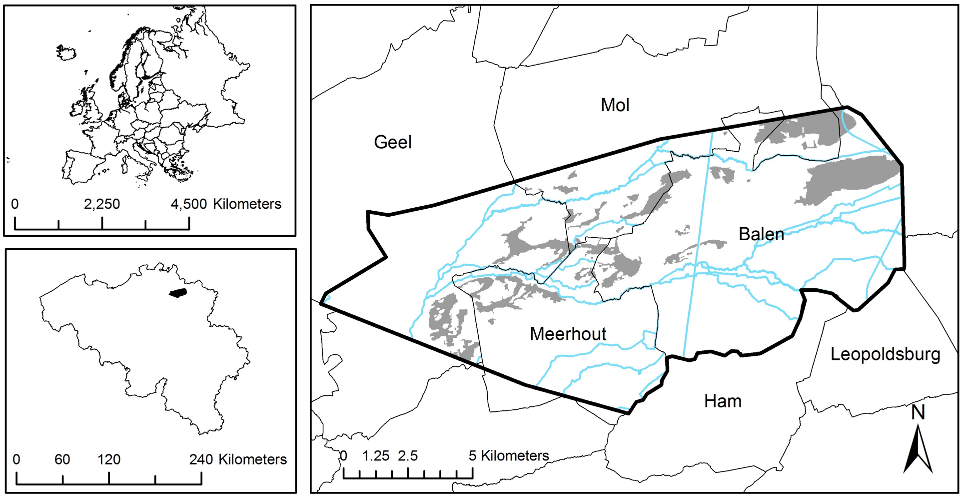


Figure 5.3: Location of Belgium within Europe (top left), location of the study area within Belgium (bottom left) and a map of the Belgian Land dune region (right) depicting the inland dunes (grey) and the major streams (blue) in the area.

5.2.3 Case study application

To illustrate the functionalities of the developed plug-in, the model, described in the previous chapter, was applied on a small study area (160 km^2), located in the Campine Region in the upstream part of the Grote Nete basin in Belgium (Figure 5.3). The area consists of a series of inland dune relicts covered with monotonous pine plantations, mixed forests, heather and bare soil. The area is intersected by numerous brooks and meandering streams with adjacent valley wetlands. Although the area is located in the densely populated northern half of the country, it is known for its high quality nature and rural characteristic.

Although all six services that were considered in the previous chapter are relevant within this study area as well, only maps for soil organic carbon storage as an indicator for the ES climate regulation are presented to illustrate the functionalities of the plug-in and the decision support capacity of the maps it generates. In the study area, an important amount of carbon is being stored in the soils, especially along the river valleys covered with marsh grassland and brook forests. The modelled and mapped carbon stocks represent the potentially attainable stock, expressed in ton.ha^{-1}. Note that this differs from the yearly carbon stock gains in soil and biomass which were modelled in the previous chapter as an indicator for the ES climate

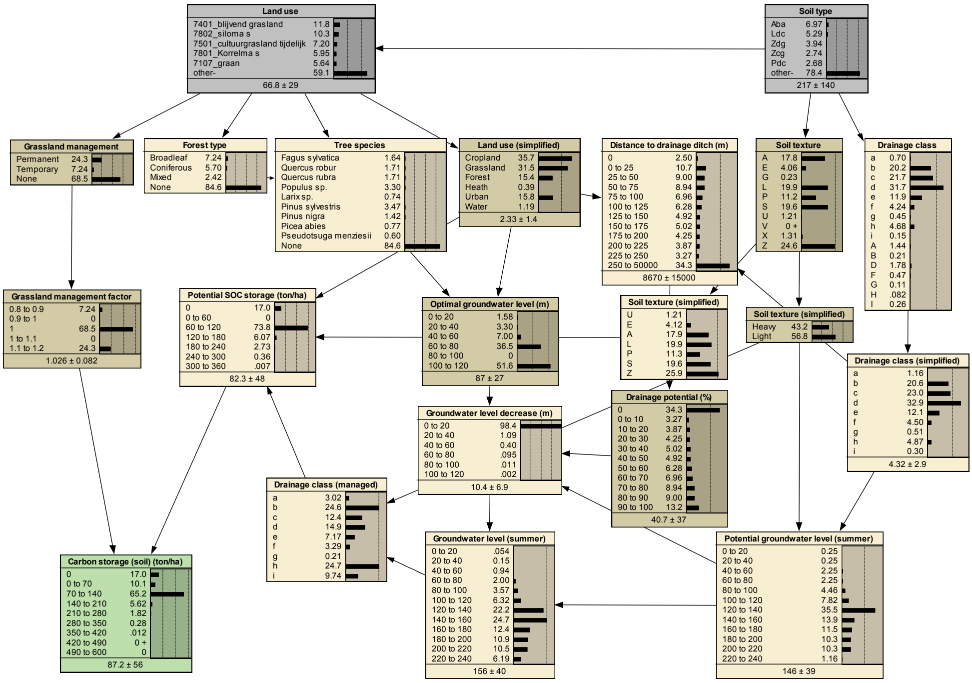


Figure 5.4: Bayesian belief network model to model soil organic carbon stock as an indicator for the ecosystem service climate regulation. This network is a subnetwork of the model presented in chapter 4. Input and output nodes are coloured grey and green, respectively.

regulation. The applied model, derived from the model presented in the previous chapter, is presented in Figure 5.4.

5.3 Results and discussion

5.3.1 Uncertainty maps

Conventional BBN output maps

The first four output maps, produced by the plug-in, spatially visualise the expected ES delivery (quantity maps) and the uncertainties associated to these predictions (uncertainty maps) on separate maps (Figure 5.5). While maps representing the most probable state and the probability of that state are more intuitive and thus probably preferred by laymen, scientists are generally more confident with the expected value and standard deviation approach. An important drawback of the latter approach is its incompatibility with models that contain output nodes whose states are only qualitatively defined. Besides, standard deviation maps are less informative in case the predicted distributions are skewed. People usually tend to assume an unskewed distribution while interpreting standard deviation values. This may result in unintended map interpretation. For example, in case the standard deviation is higher than the expected value, map readers may assume that negative values are probable as well, which may not be the case for a skewed distribution (see Table 5.1). A major disadvantage of the other approach is that the probability of the most probable state can only be interpreted relatively, taking into account the number of states of the output variable. A large number of states in the output node of the network will increase the chance for low probabilities in the uncertainty layer. The standard deviation as a measure for uncertainty, on the other hand, is not sensitive to changes in the number of states of the output node. Standard deviation and expected value maps are thus preferably chosen for quantitative output variables (preferably with an unskewed distribution), while maps representing the most probable state and associated probability are preferred to visualise qualitative output variables. A major weakness of these conventional BBN output maps is that information related to quantity and uncertainty are visualised on separate maps which makes map interpretation cognitively more demanding (Kubícek and Sasinka, 2011).

Sampled maps

Using map samples is a first approach to visualise both quantity and uncertainty on a single map. These map samples represent one, according to the model, possible truth. In these maps, uncertainty of the model output will be visualised on the scale of land parcels, which are defined as parts of the land that consist of a set of pixels with a common land cover and use. As pixels within one land parcel have almost the same characteristics, the model will predict a similar probability distribution for all these pixels. In case the model predictions are relatively uncertain for a particular land parcel, this parcel will be characterised with a high degree of speckle noise in the sampled maps. Thus, quantity is visualised through pixel colors, while uncertainty is represented by speckle noise (Figure 5.6). In addition to the advantage of representing both quantity and uncertainty on a single layer, these maps are also able to visualise skewness of probability distributions. In figure 5.6, for example, the sampled map is considerably darker compared to the map that represents the most probable state for each pixel. This suggests skewness of the probability distributions, for most pixels the chance for a value that is higher than the most probable state is higher than the chance for a value that is lower.

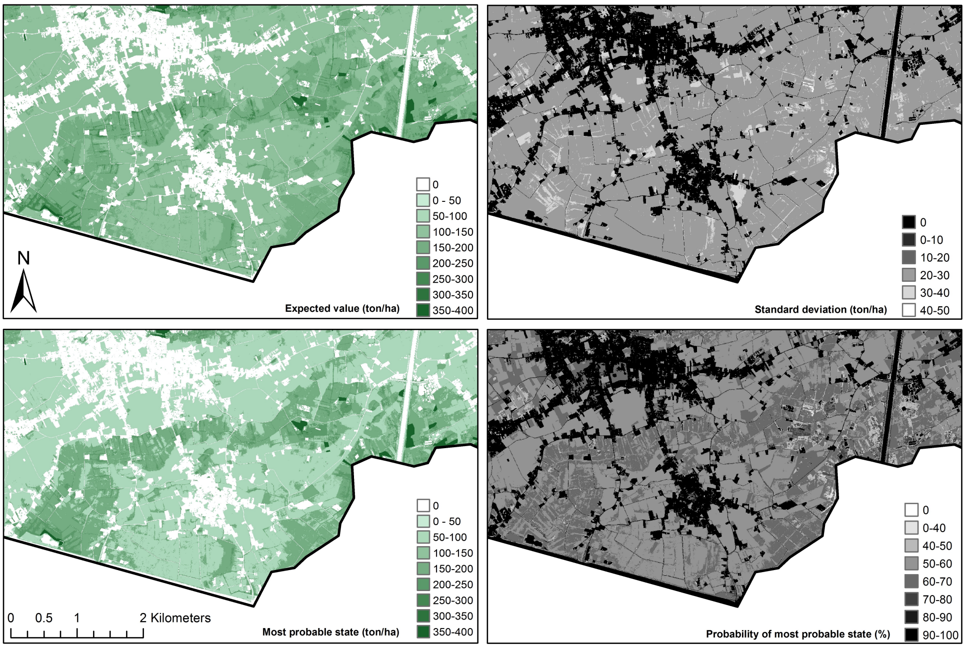


Figure 5.5: Left: Maps representing carbon stock (as an indicator for the ecosystem service climate regulation) predicted by the model as expected value (top) and most probable state (bottom). Right: maps representing the uncertainty associated to the model predictions as standard deviation (top) and probability of the most probable state (bottom). Zoom in on the southern part of the study area.

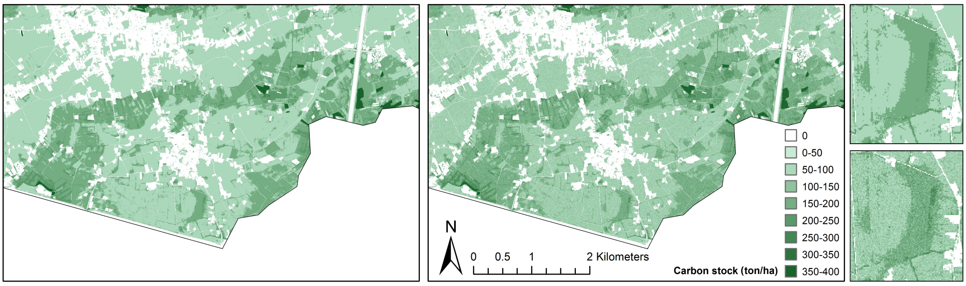


Figure 5.6: Left: a most probable state map, depicting for each pixel the predicted most probable state. Middle: a sampled map wherein each pixel represents a state that is sampled from the model's predicted probability distribution for that pixel. Right: a zoom in to visualise the speckle noise that represents uncertainty of the model predictions.

As mentioned by Uusitalo et al. (2015), decision makers generally prefer information on the entire study area rather than information on individual pixels. An advantage of sampled maps is that they can be used to infer the probability distribution of total ES delivery in the study area. The sum of all pixels of one map sample will constitute one sample of the probability distribution of total ES delivery in the study area. By sampling multiple maps and, thus, generating multiple samples of the study area's total ES delivery, the probability distribution of total ES delivery can be approximated. This distribution can be used to derive the expected value and standard deviation of the study area's total ES delivery. An important limitation of the proposed approach is the assumption that spatial autocorrelation among the study area's pixels is absent. However, within one land parcel pixel values are generally similar which violates this assumption. As shown by Canters (1997), wrongly assuming absence of spatial autocorrelation within land parcels may affect the obtained probability distribution for the entire study area. Wrongly assuming absence of spatial autocorrelation will not affect the expected value of the study area's total ES delivery but will result in an underestimation of the uncertainty associated to the study area's total ES delivery.

Ignorance maps

Figure 5.7 shows the most probable state map of the ES climate regulation without (left) and with an ignorance mask (right) that hides areas where the probability of the model's predicted most probable state is lower than 70%. As can be seen in Figure 5.7, most of the areas where the model predicts high climate regulation potential are masked denoting that these predictions are relatively uncertain. Ig-

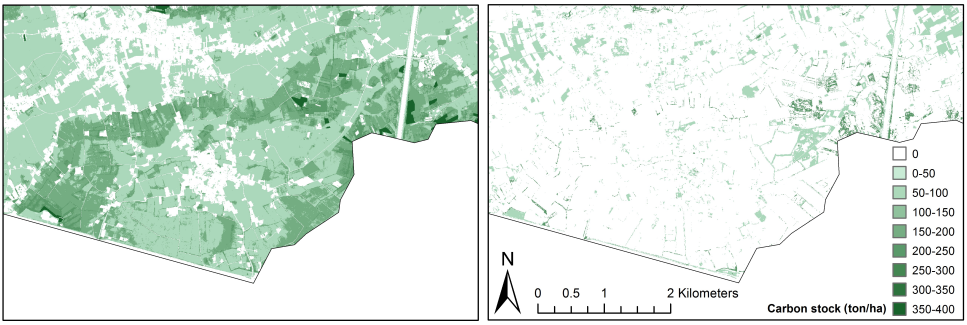


Figure 5.7: Maps depicting for each pixel the predicted most probable state without (left) and with (right) ignorance mask. The ignorance mask hides model predictions in case the probability of the predicted most probable state is lower than 70 %. Zoom in on the southern part of the study area.

norance maps can be used to focus the attention of map readers on those areas where model predictions are relatively sure. An important drawback of this method is that information is lost for those areas where uncertainty is high. As previously discussed, the probability of the most probable state highly depends on the number of states. This has to be accounted for while defining the threshold.

Cumulative probability maps

As discussed by MacEachren et al. (2005), laymen tend to simplify information related to uncertainty to simple heuristics that can support their decision making. Similarly, probability distributions can be translated into cumulative probabilities denoting the probability of exceeding a certain threshold ES delivery. The legibility of such cumulative probabilities is known to be higher than that of probability density values (Ibrekk and Morgan, 1987). This approach was also illustrated in chapter 3. In a cumulative probability map, a pixel's value is calculated as the sum of the probabilities of all the states above a certain threshold state. The cumulative probability maps (Figure 5.8) represent for each pixel the probability of exceeding the predefined ES delivery threshold. An important feature of this type of uncertainty mapping is the strong effect of the selected threshold on the output map. Probability values depend on the selected threshold and become more extreme as thresholds are more extreme (Figure 5.8). The possibility to set a threshold on the other hand allows users to focus on areas of particular interest with a certain degree of service delivery. Cumulative probabilities can also be linked to risk-averse and risk-taking behaviour. Risk-averse decision makers, which tend to minimise the probability

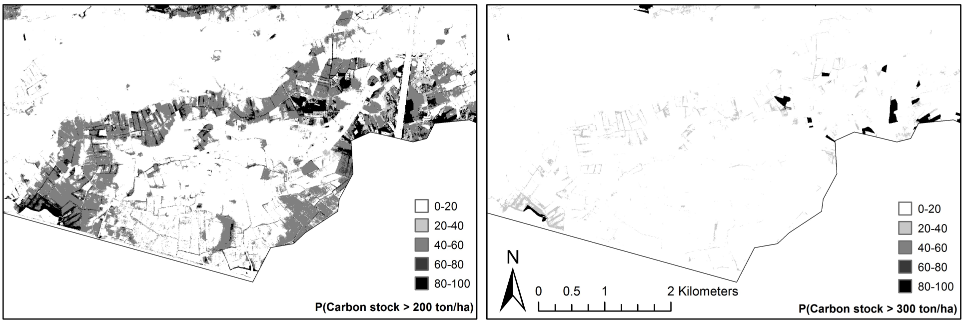


Figure 5.8: Maps depicting for each pixel the probability of attaining a carbon stock above 200 ton.ha^{-1} (left) and 300 ton.ha^{-1} (right). Zoom in on the southern part of the study area.

of low values, will be interested in cumulative probability maps produced with a lower threshold value than risk-taking decision makers, which tend to maximise the probability of very high values (Makinson et al., 2012).

Comparison of maps

The decision on which type of uncertainty map to use depends on different factors such as type of ES, type of output data (qualitative, quantitative, monetary), targeted audience, degree of uncertainty and research objectives. Table 5.2 gives an overview of the main technical advantages and disadvantages of the different uncertainty maps, allowing users to make a more informed decision on which type(s) of uncertainty visualisation to use.

5.3.2 Software framework

The plug-in, discussed in this chapter, has the potential to facilitate BBN model development and application in the ES modelling research domain. First of all, it can be used during expert-based adaptive model development. BBNs are frequently mentioned as a suitable tool to be included in an adaptive model development framework (e.g. Lynam et al., 2010; Howes et al., 2010). Aside from new data that become available, expert knowledge can be used for sequential model updating. The possibility to generate maps supports this iterative process. During this iterative process maps can be useful to identify flaws in model performance under specific biophysical conditions. Map-based model validation is a second potential application of the plug-in. As mentioned in chapter 2, model validation by experts in ES modelling

Table 5.2: Advantages and disadvantages of the different types of uncertainty maps.

Map type	**Advantages**	**Disadvantages**
Standard deviation map	-Independent of the number of states of the output node	-Only for quantitatively defined output nodes -No integration of quantity and uncertainty in one map -Less informative in case distributions are skewed
Probability map	-Straightforward interpretation -Integrates information on quantity and uncertainty in case the model's output node has two states	-Dependent on the number of states of the output node -No integration of quantity and uncertainty in one map
Sampled map	-Integrates information on quantity and uncertainty -Visualises distribution skewness	-Represented quantities potentially deviate more from expected value
Ignorance map	-Integrates information on quantity and uncertainty -High flexibility in mapping output by setting threshold value -Straightforward interpretation -Focus on most confident model predictions	-No quantitative information when the probability is below the threshold -Strong dependency on user-defined threshold
Cumulative probability map	-Integrates information on quantity and uncertainty -High flexibility in mapping output by setting threshold value -Straightforward interpretation -Close to mental heuristic for decision making	-No absolute values for ES delivery -Strong dependency on user-defined threshold

research is crucial as data for quantitative model validation are usually not available. Face validity tests, as proposed by Pitchforth and Mengersen (2013), are an example of qualitative model validation. These tests, where experts evaluate the plausibility of model outputs, can be carried out on mapped model results as well (Van der Biest et al., 2014). By using maps, experts can evaluate the behaviour of the model for multiple land uses and biophysical conditions at once.

Another important advantage of the use of BBN models in a mapping context is its high flexibility related to input data. BBN models can be easily transferred and applied in other case studies where differing spatial input data are available. A land use map, for example, usually building on a specific classification system, frequently differs among study areas. As a consequence, the original model's land use node will not be able to deal with the land use map of the new study area. Adding a new input node to the model that includes all possible classes of the new land use map can easily solve this problem. Subsequently, the causal link between this new node and the original input node can be quantified through expert knowledge. A similar model adaptation enables the use of primary data, such as satellite images, as model input. In this case, BBNs offer an additional advantage as classification uncertainty, associated to the translation of primary data to the states of the model's original input node, can be explicitly taken into account while defining the CPT of the added causal link (Hou et al., 2013).

Although the plug-in can be run similarly on input data sets with different spatial resolutions, there is a clear link between map resolution and the uncertainty of ES maps (Schulp and Alkemade, 2011). The coarser the resolution of a map, the higher the uncertainty of the mapped attributes. Especially small landscape elements that are not occurring in clusters will not be represented properly in coarse-resolution maps (Moody and Woodcock, 1996). This geometric uncertainty will increase for heterogeneous landscapes where individual pixels often cover a mix of land uses. The fact that only one land use class is assigned to these mixed pixels leads to uncertainty. If data are available on the composition of mixed pixels, for example, when maps are obtained through the use of fuzzy classification algorithms (Foody, 1996), BBNs can take this uncertainty into account and propagate it through the model. In most cases, however, this information is not available. To account for this unknown uncertainty BBNs can be adapted to produce more credible results. For example, if a BBN model that is designed to run on the Flemish land use map needs to be run on a coarse resolution European land use dataset, the uncertain link between the land use categories of both land use datasets can be explicitly integrated into the model similarly as discussed in the previous paragraph.

An important limitation of the proposed software framework is its inability to account for spatial interactions. As denoted by Hein et al. (2006), spatial interactions and scales frequently play an important role in ES assessments. Pollination, flood retention and recreational use are classic examples of ES whose delivery processes are spatially explicit. Although the software framework does not support interactions among pixels, BBNs can, to a limited extent, deal with spatial interactions by including input nodes that describe particular characteristics of the pixel's neighborhood. Landscape metrics, frequently used in landscape ecology, can, for example, do the trick (Syrbe and Walz, 2012). However, including extra input variables will increase model complexity and, hence, will increase both the plug-in's calculation time and memory usage.

At last, it needs to be mentioned that several alternative software packages exist to apply BBNs on spatial data. Examples include QuickScan, a standalone software package, developed by Verweij et al. (2014), that integrates model visualisation, interactive model exploration and spatial representation of the model output, and Geo-Netica, a geographical extension of the Netica software application (Norsys Software Corporation, 1998). However, none of them focusses on meaningful ways to cartographically represent the uncertainties associated to BBN output. Moreover, the inclusion of this tool as a plug-in within an existing GIS package offers some additional advantages over currently available stand-alone packages. As the presented tool requires spatial data, familiarity with a GIS package is a prerequisite to be able to use the tool. As QGIS is currently one of the most-used open-source packages, for most users the threshold to apply this plug-in will be low as no additional software packages need to be purchased, installed and understood. Moreover, QGIS includes numerous map processing tools that enable all necessary manipulations of input and output maps, avoiding the need to transfer spatial data across multiple software packages.

5.3.3 Open-source for continual improvement

To be able to distribute the tool, to receive feedbacks form end-users and to attract collaborators to improve the tool, the source code of the plug-in was made available on GitHub (www.github.com/DriesLanduyt/PMAT), an online platform to store software code, to exchange code and to work together on software projects. An important advantage of providing this tool as an open-source plug-in is that the tool can evolve and improve as a result of interactions among end-users and software developers. In the context of this plug-in, this process may, for example, lead to end-users suggesting alternative approaches or indicators to map uncertainty which can, in turn, be implemented by software developers that are working or want to work on the project. Although this may lead to several parallel attempts, carried out by different developers, to improve the code, merging successful extensions into the original code will, in the end, improve the decision support capacity of the plug-in and the maps it produces. Since its launch in June 2015, nine researchers from around the world already expressed interest in using the plug-in in their own research field. Although the GitHub page allows users to suggest potential improvements or to improve the code themselves, up till now, these functions have not been employed.

5.3.4 Beyond the ecosystem services research domain

Although this thesis focusses on the use of BBNs in ES assessment studies, the ability of BBNs to transparently deal with uncertainties, a universal aspect across a broad range of research domains (Uusitalo et al., 2015), promotes its use in a wide range of applications, ranging from medical diagnosis (Kahn et al., 1997), machine learning (Ordóñez Galán et al., 2009), classification problems (Aguilera et al., 2010), to environmental modelling and management studies (Aguilera et al., 2011). A subset of these research domains also deal with spatial data. Aside from ES assessments, popular spatial BBN applications include habitat suitability mapping (Smith et al., 2007), image classification in remote sensing (Park and Stenstrom, 2006), spatial multi-criteria analysis (Stassopoulou et al., 1998) and risk assessment (Grêt-Regamey and Straub, 2006). The QGIS plug-in, discussed in this chapter, may complement current spatial BBN studies by bridging the gap between science and decision support by spatially representing the output of these studies in a meaningful way. Moreover, the plug-in may promote the use of BBNs as an alternative approach to analyse uncertainties in spatial analyses far beyond the ES research domain (e.g. Ligmann-Zielinska and Jankowski, 2014).

5.4 Conclusions and recommendations

The developed QGIS plug-in promotes the use of BBNs to model and map ES delivery. BBN models can add value to current ES mapping research as they enable the integration of uncertainties and expert knowledge in spatial ES accounting studies. However, interpretation of mapped uncertainties remains a challenging task. In this chapter, several mapping approaches were discussed, tailored to probabilistic BBN output, to facilitate interpretation of mapped uncertainties and to support decision making based on mapped uncertainties. Clearly, no one-fits-all visualisation approach exists. Depending on whether the output variable is qualitatively or quantitatively defined, the cognitive capacity of the map reader and the questions that need to be answered, different visualisation approaches are needed.

In management domains that predominantly rely on expert opinion for decision making (as no other information is available), this tool may be extremely useful as it offers a structured and standardised approach to include expert knowledge into spatial analysis and decision support.

6 Socio-economic impacts on ecosystem services and the role of uncertainties

Economic growth and the rapid increase of the earth's population has led to changing environments all around the world. In Flanders, this change is being manifested predominantly through land use change, an important precursor for a broad range of rising problems, such as, loss of biodiversity, environmental pollution and a decline of natural and semi-natural landscapes. This also leads to changes in ecosystem services being delivered, such as, wood production, pollination of agricultural crops and climate regulation by carbon sequestration. Although general global trends have been revealed (Costanza et al., 2014; MEA, 2005), the effects of alternative socio-economic developments on future ecosystem service delivery in Flanders remains largely unknown. Projecting ecosystem service delivery rates is, however, challenging as a lot of uncertainties need to be taken into account. Uncertainties arise from uncertain socio-economic developments, uncertain effects of these developments on land use change and, as discussed previously, uncertainties associated to ecosystem service delivery processes. This chapter investigates the potential of Bayesian belief networks to propagate the uncertainties of land use change predictions to obtain regional estimates of ecosystem service delivery rates and the uncertainties attached to these predictions.

This chapter is based on:

Landuyt, D., Broekx, S., Engelen, G., et al., Submitted. The impact of alternative socio-economic developments on ecosystem services in Flanders - Shedding light on an uncertain future. Science Of The Total Environment.

6.1 Projecting ecosystem service delivery

As discussed in chapter 4, land use is one of the most used proxies for ES assessment at the regional scale. Land use is used as sole indicator or alongside other variables, such as, soil type and hydrology to assess ES delivery. Also when assessing the impact of alternative socio-economic development scenarios on ES delivery land use change is one of the most considered processes. These socio-economic impact assessments, frequently referred to as regional scenario analyses, thus require a two-step approach, a combination of land use change modelling and ES delivery modelling. This two-step approach has been followed in several studies (e.g. Baral et al., 2014; Geneletti, 2013; Bateman et al., 2011; Nelson and Daily, 2010). In these studies, land use change projections for several alternative futures were obtained through participatory processes (Baral et al., 2014; Bateman et al., 2011) or rule-based GIS models (Geneletti, 2013; Nelson and Daily, 2010). Other frequently used techniques to model land use change include agent-based models and cellular automata (Nelson and Daily, 2010).

Although the uncertainty associated to the outcome of such coupled component models is usually high due to uncertainty propagation from one model component (land use change model) to the other (ES model), uncertainties are generally not accounted for explicitly (Kelly (Letcher) et al., 2013). Uncertainty assessment is generally limited to model testing by using, for example, sensitivity analyses (e.g. Tianhong et al., 2010). Nevertheless, quantification of uncertainties is necessary because certainty of the model output may be a central criterion to choose among several alternatives (Uusitalo et al., 2015) and may determine the robustness of this choice (Dessai and Hulme, 2007). The inability to account for uncertainties in over-parameterised coupled component models may explain the lack of studies that have accounted for uncertainties in the past (Kelly (Letcher) et al., 2013).

As discussed previously, BBN models are able to account for uncertainties more easily. Their recent introduction in the environmental modelling domain (Aguilera et al., 2011) has led to more explicit accounting for uncertainties in diverse environmental studies, such as, risk assessments (Ban et al., 2014), spatial multi-criteria analyses (Stassopoulou et al., 1998) and habitat suitability modelling (e.g. Smith et al., 2007). BBNs have been used as well for land use change modelling, most of the time in combination with other modelling techniques. They are being used either to predict landowners' decisions affecting future land use (e.g. Kocabas and

Dragicevic, 2007; Bacon et al., 2002; Aalders, 2008), or to be able to incorporate probabilistic rules in cellular automata or rule-based land use change models (e.g. Krüger and Lakes, 2014). Thus, BBNs have been used for both ES delivery modelling (chapter 2) and land use change modelling. However, studies that include both applications in one integrated model are rare (Haines-Young, 2011). A reason for that might be that BBNs (in isolation) are less suitable to model land use change compared to existing techniques, such as, cellular automata. This low suitability of BBNs can be ascribed to the fact that BBNs may become overly complex and hard to compile on standard computer systems when spatially explicit processes are being considered (Giretti et al., 2012), processes that generally drive land use change.

In this chapter, a methodology is presented that explicitly accounts for uncertainties while assessing future ES delivery. The presented approach combines BBN models to assess ES delivery with a cellular automaton to model land use change. The use of BBNs enables straightforward propagation of uncertainties through the coupled component model. By applying the integrated model, future ES delivery in Flanders, Belgium is evaluated for four alternative socio-economic development scenarios. More specifically, this chapter investigates whether taking into account uncertainties may influence policy recommendations that are typically inspired by such scenario analyses. On top, the added value of propagating land use uncertainty in this specific case is being assessed by analysing whether the effect of this additional source of uncertainty is substantial and is not overruled by the high uncertainties inherently present in ES models.

6.2 Methods

6.2.1 The Flemish region as study area

The entire Flemish region was chosen as study area for this analysis. As the responsibility for spatial planning shifted from the national to the regional government in 1980, scenario analyses to support spatial planning are typically carried out on this scale. During the last decades, land use change in Flanders has resulted in a decline in open spaces and natural landscapes. Land use change has been predominantly driven by unstructured urban sprawl that can be attributed to a sequence of events: industrialisation, the development of a dense tram and train network in the beginning of the 19th century, the rise of car use after World War II, the absence of national policies to steer spatial development between 1945 and 1962 and weak spatial planning regulations introduced after 1962 (De Decker, 2011). The region's history of intense urban sprawl, its high population density and the commitments made to the European Union, in accordance with the EU NATURA2000 Directive, to develop a network of protected areas make the development of sustainable spatial planning regulations a challenging task for the Flemish government. Detailed information on the Flemish region can be found in section 4.2.1.

6.2.2 Four futures for Flanders

European countries are all facing similar challenges which governments need to deal with in the coming years. Although international organisations such as the European Union and the World Trade Organisation (WTO) have proven to be economically beneficial, decision making at the international level is getting more and more complex. In addition, European countries are facing local problems related to ageing, income inequality and increased social heterogeneity. To react upon these two broad categories of challenges, governments may follow different routes. To explore potential pathways to solutions and to compare the consequences of alternative socio-economic developments, long-term scenario analysis can be extremely useful. On the scale of Europe, four possible futures have been defined by de Mooij and Tang (2003). These scenarios were structured according to two axes which represent driving forces that are highly uncertain and that may have a considerable impact (van 't Klooster and van Asselt, 2006). In this scenario analysis, strategies to react upon the previously discussed challenges were chosen as axes: International cooperation versus National sovereignty and a focus on private responsibility versus a focus on public responsibility. Similar dimensions have been used in other scenario analyses (e.g. UK socio-economic scenarios (Berkhout et al., 2002)) and for the development of emission scenarios by the Intergovernmental Panel on Climate Change (IPCC) (Nakicenovic et al., 2000). The use of these dimensions instead of fixed scenarios makes it possible to develop specific scenarios for different national contexts while still being able to compare the outcomes across different countries.

As visualised in Figure 6.1, the Global Economy (GE) and the Strong Europe (SE) scenarios refer to futures with international cooperation and a focus on private and public responsibilities, respectively. The Transatlantic Market (TM) and Regional Communities (RC) scenarios refer to futures without international cooperation and a focus on private and public responsibilities, respectively. These scenarios have been translated into national scenarios for the Netherlands (CPB et al., 2006), and later, into a regional scenario for Flanders (Kuhk et al., 2011). This translation in-

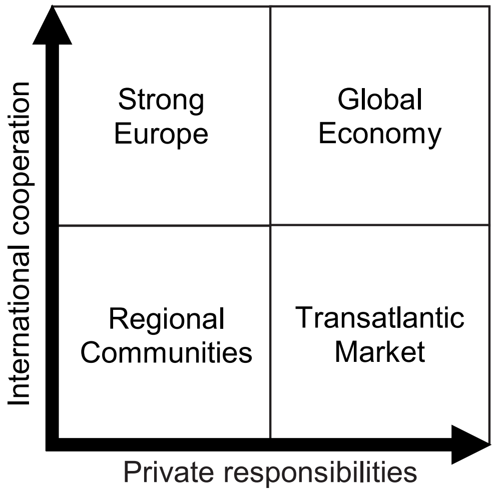


Figure 6.1: Four potential socio-economic development scenarios arranged according to their main characteristics: International cooperation and private responsibility.

Table 6.1: Qualitative comparison of the studied scenarios with indications of growth (+) and decline (-) for several indicators compared to their status in 2010

	Global Economy	**Transatlantic Market**	**Strong Europe**	**Regional Communities**
Population	+ +	-	+	- -
Agriculture	-	-	+/-	+/-
Industry	+	+/-	+/-	-
Forestry	+/-	+	-	+/-
Natural areas	+ +	+	+ + + +	+ + +
- Focus on biodiversity	-	-	+	+/-
- Focus on recreation	+	+	-	-

cluded defining region specific population growth rates, employment degrees, nature conservation aims, etc. for each scenario. A qualitative comparison of the scenarios is provided in Table 6.1.

6.2.3 Modelling land use change between 2010 and 2050

The impact of these scenarios on future land use was modelled using a constrained cellular automata land use change model, developed by White and Engelen (1993) and calibrated for the Flemish region by Engelen et al. (2011). The model features a layered structure consisting of a global, a regional and a local level, representing the fact that processes driving land use change occur at different spatial resolutions. The three levels are intimately linked: growth figures are exchanged as drivers or constraints. The model at the global level represents the regions Flanders and Brussels as one entity. It includes population growth trends, trends in the amount of jobs in 12 aggregated economic sectors, and acreages allocated to the different natural and agricultural land uses in the model. At the regional level, a spatial interaction based model is used to represent the competition for residents and jobs (in the same 12 aggregated economic sectors) among 23 arrondissements. It computes for each arrondissement the total amount of residents and jobs in the 12 economic sectors, their average density, and thus determines the demand for land of the associated land use classes. At the local level, a cellular automaton is used that represents the regions Flanders and Brussels as a regular grid of 1.35 million cells of 1 hectare each. For each cell, the assigned land use (37 possible classes) depends on spatial interactions with other land uses in its neighbourhood, a circular area with a radius of 8 cells, and three more static characteristics of the cell: its accessibility, its physical suitability and the zoning status that either facilitate or exclude the establishment of a particular land use. Spatial interaction rules within the neighbourhood (distance-dependent repulsion and attraction among land uses), accessibility, suitability and zoning status are all land use specific characteristics. The model is calibrated and validated and is used to predict land use change between 2010 and 2050 for the scenarios discussed in the previous section. A detailed description of the land use change model can be found in the work of White et al. (2015). More information on how the model was calibrated for the Flemish region can be consulted in the work of Engelen et al. (2011).

To assess the uncertainty associated to the predicted land use maps, the land use change model was ran several times with a randomly chosen value for one specific parameter of the model. The chosen parameter, which operates at the local level of the model, represents the degree of irrationality in human behaviour when initiating a specific land use change. Thus, for each scenario, a set of potential future land use maps was obtained. As the chosen parameter operates at the local level, the outcome uncertainty represents the uncertainty for a given set of parameters and driving forces that operate at a higher level in the model. The obtained set of raster layers can be converted into a single probabilistic layer with for each cell a probability distribution over different land use classes. Thus, the combined raster layer represents for each cell the probabilities of belonging to particular land use classes. The uncertainty associated with each cell was assessed using an entropy measure (based on information theory) ranging between 0 (land use type is highly uncertain) and 1 (land use is deterministically defined), referred to as posterior probability certainty index (PPCI) by Marcot (2012). This index is calculated by

Equation 6.1 with n the number of land use classes and P_i the probability of land use class i.

$$PPCI = 1 + \frac{\sum_{i=1}^{n} P_i * ln(P_i)}{ln(n)} \tag{6.1}$$

To compare land use changes across scenarios, the expected change for each land use type relative to its current extent was calculated using Equation 6.2 with i≠j, $n_{j \to i}$ the number of cells that are likely to change from land use j to land use i, $P_{j \to i}$ the average probability of that shift and $n_{i,0}$ the amount of cells that are currently covered by land use i.

$$EC(LU_i) = \frac{\sum_j (n_{j \to i} P_{j \to i}) - (n_{i,0} - n_{i \to i}) * (1 - P_{i \to i})}{n_{i,0}} \tag{6.2}$$

6.2.4 Modelling ecosystem service delivery

The regional model, discussed in chapter 4, makes use of the most recent and detailed land use map of Flanders (Poelmans and Van Daele, 2014). However, the applied land use change model does not predict land use change as detailed as this land use map. Therefore, the ES delivery model needed to be adapted to make it compatible with the land use classification system of the land use change model. As discussed in the previous chapter, this can be done relatively easily by including an extra node that contains as states all land use types of the new classification system. Figure 6.2 represents the part of the model that was adapted. By also keeping the more detailed land use node in the model, more detailed predictions could be made based on the predicted land use class (lower detail) and the soil type. For example, while the land use change model only predicts two types of forests (forests with nature management and forests with forest management), by keeping the original land use node and its relation to soil type in the model, the BBN can predict more detailed forest types and, thus, can predict ES delivery more accurately. To give an example, when the land use change model predicts forest with forest management on dry sandy soils that forest will have a higher probability of being a pine stand than a popular stand. The adapted model accounts for these relations based on current relations between soil type and land use.

For this analysis, four out of the six ES that are discussed in chapter 4 were selected. Drinking water production was not considered as the delivery of this service

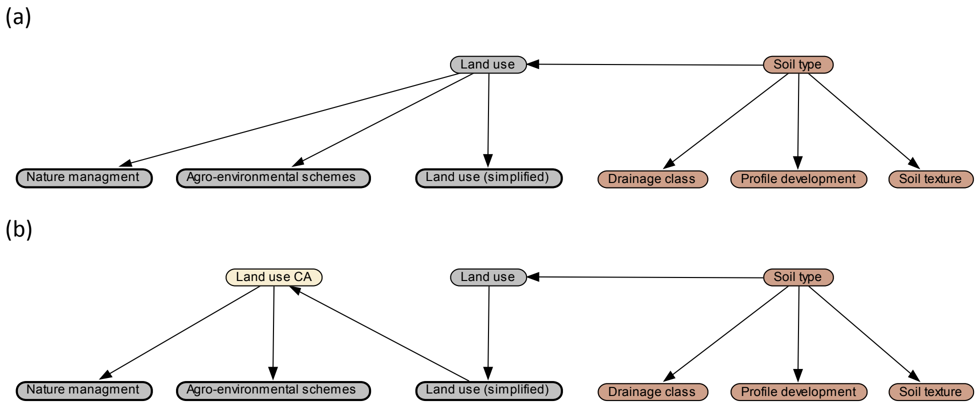


Figure 6.2: Adapting the original model (a) to make it compatible with the output of the land use change model (b). The 'Land use CA' node represents the land use classification system of the cellular automaton land use change model.

is affected by spatial allocation of sewage infrastructure, an attribute that could not be predicted by the land use change model. The ES soil formation was omitted as well due to its close link with soil organic carbon storage. This resulted in a final set of two provisioning services (food production and wood production) and two regulating services (air quality regulation and climate regulation). To be able to compare future trends among the delivery rates of the different services, all services were expressed in monetary terms.

The monetary value of carbon sequestration can be derived from the costs associated to a temperature rise that can be avoided due to a reduction in atmospheric CO_2 concentration. As discussed in chapter 4, woody biomass and soils were both considered as potential sinks for carbon sequestration. Carbon sequestration in the soil depends on both the soil organic carbon stock in 2010 and the expected equilibrium soil organic carbon stock in 2050. Therefore, both the current land use and the predicted land use in 2050 needed to be included as nodes in the model. Yearly soil organic carbon gains were subsequently calculated as the difference between both estimates, divided by 100, assuming that soils reach their equilibrium SOC concentration after a period of 100 years. Although it is known that the length of this period is highly variable (Kirschbaum et al., 2001), a period of 100 years was used as a save estimate to avoid potential overestimations. The organic carbon storage in the soil is subsequently summed with the organic carbon storage in woody biomass and multiplied with an avoided abatement cost of €20.ton^{-1} CO_2 or €73.2.ton^{-1} C (Aertsens et al., 2013).

To estimate the monetary value of air quality regulation, an avoided health damage cost estimate of €54 kg^{-1} PM_{10} was used. This value was obtained as a weighted average of the avoided health damage costs associated to $PM_{2.5}$ reduction (€150 kg^{-1}) and PM_{10} reduction (€25 kg^{-1}) (De Nocker et al., 2010). Weighting was based on the share of $PM_{2.5}$ (23%) and PM_{10} (77%) in the total amount of captured fine particulate matter. These shares are estimated based on the vegetation's capture efficiency for both PM compartments (capture efficiency for $PM_{2.5}$ is 5 times lower than capture efficiency for PM_{10}) and the concentration of both PM compartments in the air (60 and 40%, for $PM_{2.5}$ and PM_{10}, respectively). Similar estimates for both parameters were used by Vos et al. (2013).

6.2.5 Model coupling

To predict future delivery of ES, projected land use, as an output of the land use model, was used as input for the BBN models that predict ES delivery. The BBN models were ran on each cell independently, resulting in probabilistic raster layers for each ES. To investigate the influence of uncertainty propagation, both a deterministic and a probabilistic land use map, respectively obtained through one run and multiple runs of the land use model, were used as input for the BBN models. This results in two alternative runs of the coupled model, hereafter referred to as the deterministic run and the probabilistic run, respectively. The workflow is schematically represented in Figure 6.3.

To shorten calculation time, BBN models were converted into look-up tables that list for each combination of the model's input nodes' states the probabilistic output (see section 5.2.2). These look-up tables could also be used for uncertain inputs by using Equation 6.3.

$$ES\ Delivery = \sum_{i=LU_1}^{LU_n} P(i) * lookup(i, Soil\ type) \tag{6.3}$$

For input nodes of the BBN model for which no 2050 data were available, prior distributions were used. By omitting these variables while developing the look-up table, the uncertainty associated to the prior distributions was immediately integrated into the probabilistic output of the table. This feature is an important advantage of using BBNs for model coupling as it allows, by introducing additional uncertainty, model coupling in case not all inputs of the second model component could be predicted

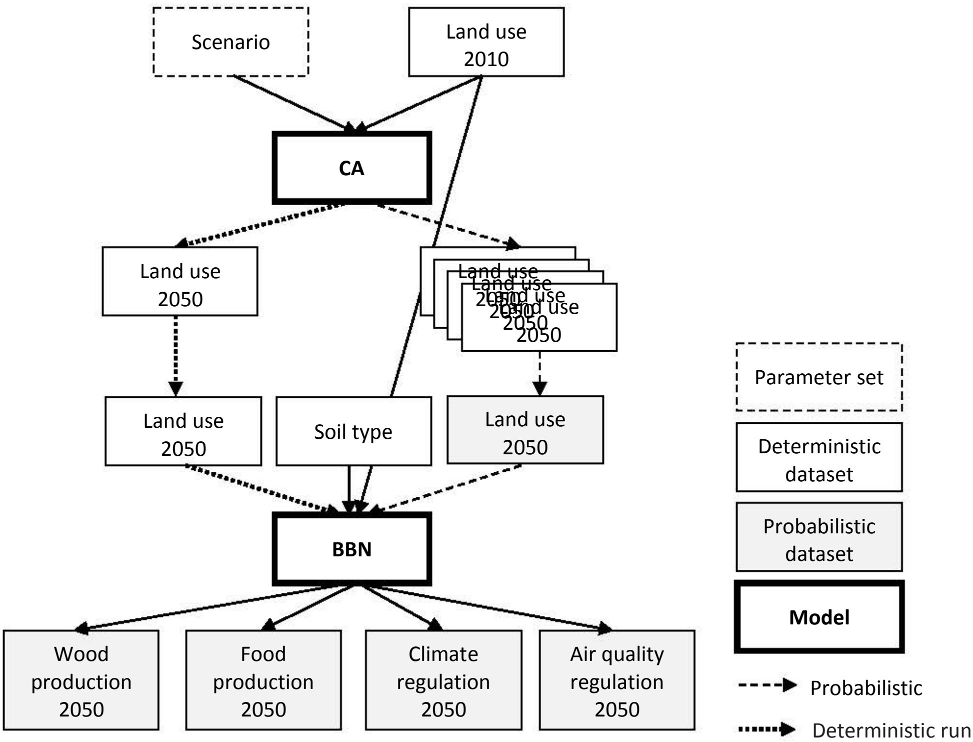


Figure 6.3: Workflow to assess future ecosystem service delivery and associated uncertainties. Bold boxes represent model components, white boxes represent regular raster data layers and grey boxes represent probabilistic raster data layers with a discrete probability distribution for each cell. CA and BBN stand for cellular automaton and Bayesian belief network, respectively.

by the first model component.

6.2.6 Regional aggregation of model output

To compare the alternative socio-economic development scenarios based on ES delivery at the regional level, the results obtained for each cell need to be regionally aggregated. Usually, this is done by summing the values of all cells in a region. Although this approach could have been applied as well in this study by summing the expected value for each cell, it would have resulted in loosing information on uncertainty. Therefore, a Monte Carlo simulation was used to repeatedly sample total regional delivery. For each sample of the regional sum, cell values for all cells in the region were sampled from their probability distribution and, subsequently, summed. An important limitation of the proposed approach is the assumption that spatial autocorrelation among the study area's cells is absent. However, within one land parcel or field, values are generally similar which violates this assumption. As already discussed in chapter 5, wrongly assuming absence of spatial autocorrelation within land parcels may affect the probability distribution for the entire study area (Canters, 1997). Wrongly assuming absence of spatial autocorrelation will not affect the expected value of the study area's total ES delivery but will result in an underestimation of the uncertainty associated to the study area's total ES delivery. As an alternative, Canters (1997) proposes field-based aggregation instead of raster-based aggregation. Field-based aggregation assumes a high spatial autocorrelation within one field. However, the difference between both approaches decreases for lower raster resolutions as for lower resolutions the surface of a cell will approximate the surface of a field. As the raster layers applied in this study have a spatial resolution of 100 meter, raster-based aggregation was applied. The amount of samples necessary to obtain a stable estimate of the distribution of total regional ES delivery was determined through simulation. After 10000 random samples, additional samples did not further influence the characteristics of the distribution of total regional ES delivery (Figure 6.4).

6.3 Results

55% of the cells, hereafter referred to as the dynamic cells, are confronted with a potential land use change (probability higher than zero) in one of the scenarios studied. Considering only the deterministic land use change predictions, this percentage decreases to 33%. Figure 6.5 represents the expected land use change under the four

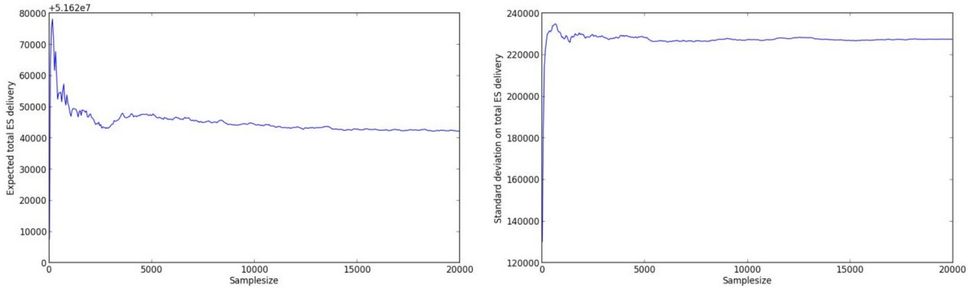


Figure 6.4: Stability plot visualising the effect of sample size on the expected value and standard deviation of the sampled distribuition of total regional ES delivery. After 10000 samples, the characteristics of the sampled distribution stabilise.

development scenarios. These regional trends correspond with the observed land use change in the deterministic land use change predictions. The two scenarios typifying reduced government control are characterised by a high urbanisation rate with an increase of urban area between 13 (TM scenario) and 23 (GE scenario) percent. The other two scenarios are characterised by an expansion of natural areas. This expansion is strongest in the SE scenario and is slightly lower in the RC scenario, mainly due to strong persistence of agricultural area in the latter. The expansion of natural areas is the lowest in the TM scenario with a reduction of naturally managed forests and heathlands. Unlike global trends, forested area is likely to increase in Flanders as the result of policies oriented to nature conservation.

The right side of Figure 6.5 represents the mean probability of newly assigned pixels for specific land use types as an indicator of the uncertainty associated with the output of the land use model. As can be derived from this bar plot, the uncertainty associated with land use allocation differs across land use types. The land use change model allocates, for example, naturally managed wetlands and heathlands with a higher certainty than it allocates agro-environmental scheme implementation. A logical finding as agro-environmental scheme implementation is predominantly driven by decisions of individuals that are hard to predict and less by the suitability of the land or by zoning regulations.

The mean PPCI values of the predicted land use maps' cells, tabulated in Table 6.2, suggest that the different scenarios hardly differ in terms of uncertainty of the model output.

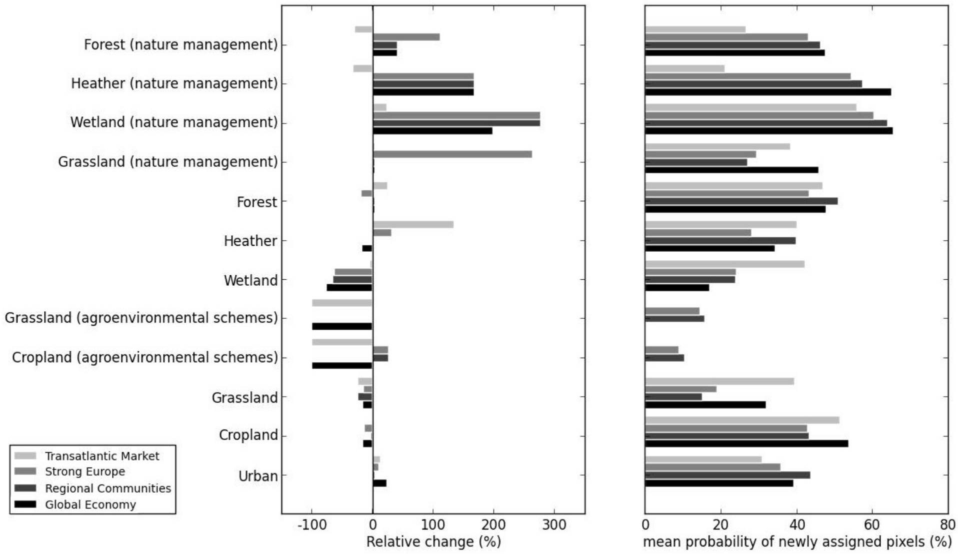


Figure 6.5: Left: expected land use change in the four scenarios expressed as percentage increase/decrease relative to the land use in 2010 . Right: land use allocation uncertainty expressed as the mean probability of newly assigned cells per land use type. Urban represents an aggregation of all urbanised land use types predicted by the land use change model.

Table 6.2: Mean posterior probability certainty index (PPCI) of the cells of the predicted land use maps representing the uncertainty related to the predicted land use map for each scenario.

	Mean PPCI$_{\textbf{all cells}}$	**Mean PPCI$_{\textbf{dynamic cells}}$**
Global Economy	0.961	0.931
Transatlantic Market	0.970	0.946
Strong Europe	0.961	0.930
Regional Communities	0.970	0.945

Table 6.3: Results of the sensitivity analysis of the ES models expressed in relative variance reduction.

	Relative variance reduction (%)			
	Food production	**Wood production**	**Climate regulation**	**Air quality**
Land use	66	44.4	40.9	80.5
Soil texture	4.43	0.884	0.924	0
Drainage class	5.52	0.495	0.636	0
Profile development	4.69	1.37	1.32	0

6.3.1 Expected ecosystem service delivery

To investigate the relative importance of the input variables soil type and land use, a sensitivity analysis of the adapted regional model was carried out. The results of this sensitivity analysis, expressed as relative variance reduction (ranging between 0 and 100) are represented in Table 6.3. The land use variable in the table represents the newly introduced land use variable. Soil type is characterised in the model by soil texture, drainage class and profile development. As can be deduced from this table, ES delivery is affected most by land use, in accordance with the findings in chapter 4.

After running the models on the predicted land use maps, ES delivery maps for four alternative futures were obtained. Figure 6.6 represents the cumulative probability distribution of total regional delivery of each ES for each scenario, obtained through aggregation of the predicted ES delivery maps as described in section 6.2.6. GE, the scenario with the highest urban expansion, is characterised by low ES delivery. Only for wood production, the scenario scores moderately compared to the other scenarios. Surprisingly, the opposite holds for the TM scenario which is also an urban growth scenario: high delivery for most services, except for food production. Similar scenario rankings are observed for the services climate regulation and air quality regulation which denotes a synergy between the delivery of both services. Both services benefit from an increase in forested areas combined with a relatively low expansion of urban areas. Also for wood production similar trends can be observed. However, as this service is not negatively affected by urban expansion for a given increase of forested areas, the GE scenario scores better for this ES. Focussing on food production only, the scenarios rank slightly differently. Logically, food production is low for urban growth scenarios. However, further implementation of agro-environmental schemes under the SE scenario results in negligible differences between this scenario and the TM scenario, one of the urban growth scenarios.

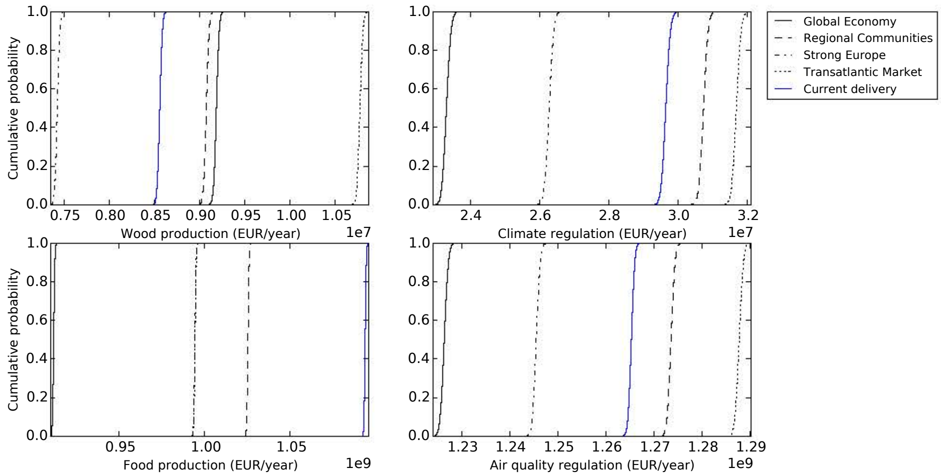


Figure 6.6: Cumulative probability curves representing the probability distributions of regional ecosystem service delivery in the four scenarios.

The steepness of the curves in Figure 6.6 indicates that the uncertainties related to the predicted total regional delivery are rather low compared to the differences between scenarios. Hence, the added value of accounting for uncertainties is small when the objective is to distinguish among scenarios. However, taking into account uncertainties may become important when comparing wood production in the TM scenario and the SE scenario. While the expected values may differ, the distributions clearly indicate the absence of significant differences between both scenarios (see also Figure 6.9).

To illustrate the model results spatially, as an example, the projections for the ES food production in the SE scenario are presented in Figure 6.7. Although the land use maps clearly visualise an increase of urbanised areas around the city of Antwerp, the effects on food production are not that pronounced. The maps also illustrate the large difference between the amount of uncertainty related to the land use maps and the amount of uncertainty related to the ES production maps, expressed as the cells' PPCI.

6.3.2 Local and regional effects of uncertainty propagation

Uncertainty propagation generally causes an increase of uncertainties along the line of propagation. Figure 6.8 represents this increase as the average decrease of the

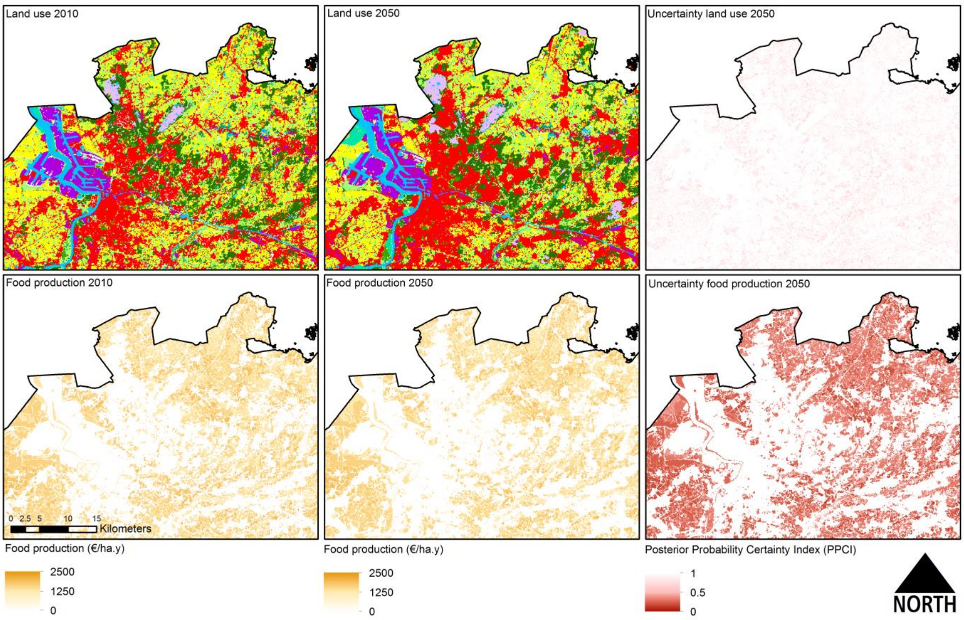


Figure 6.7: Mapped outcomes for the highly urbanised area East of the city of Antwerp for the ecosystem service food production in the Strong Europe scenario. Above: current land use (left), projected land use (middle) and the uncertainty linked to the projected land use (right). Below: current food production (left), projected food production (middle) and the uncertainty linked to the projected food production (right). Agricultural land, forests, urban area and industry are respectively coloured yellow, green, red and purple in the maps that represent land use in 2010 and 2050.

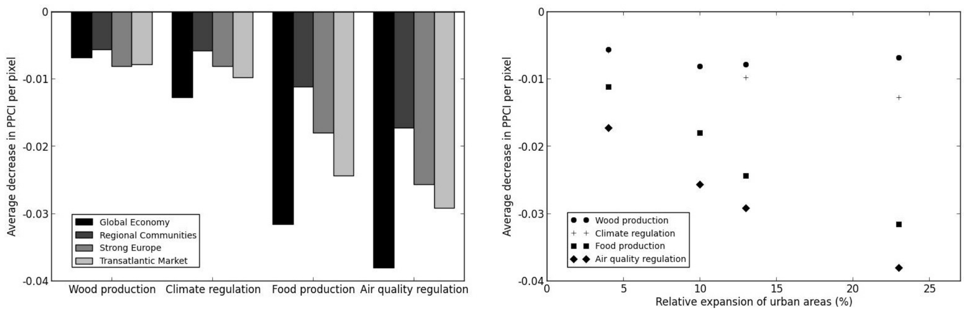


Figure 6.8: Average per cell decrease in PPCI of the ES delivery maps resulting from a probabilistic run (left), and its relation with urban expansion (right).

PPCI values of the ES maps' individual cells when the model is run probabilistically instead of deterministically. As shown in Figure 6.8, the uncertainty of the ES production maps increases only slightly when uncertain instead of deterministic land use change predictions are used as input for the BBN models. The average decrease in PPCI for each service accords with the sensitivity analyses of the models (Table 6.3). The more sensitive a service is to land use, the higher the decrease in PPCI. The increase of uncertainty is the highest for the GE scenario and the lowest for the RC scenario. The ranking of the scenarios based on this increase does not correspond with the ranking of the scenarios based on the degree of uncertainty linked to the probabilistic land use maps (Table 6.2). Instead, ranking corresponds to the degree of urban expansion in each scenario (Figure 6.8, right panel). For wood production this relation is less pronounced.

The uncertainty related to regional estimates of ES delivery also increases only slightly for the probabilistic run compared to the deterministic run. Figure 6.9 illustrates this for the ES food production for the SE and TM scenarios. The projections for food production in both scenarios were almost indifferent, a situation in which not accounting for land use change uncertainty might result in different policy recommendations. Although the probability distribution are slightly sharper for the deterministic run (top left panel in Figure 6.9), these difference are clearly too small to influence decision making. Similar small increases of uncertainty were found for the other services and scenarios.

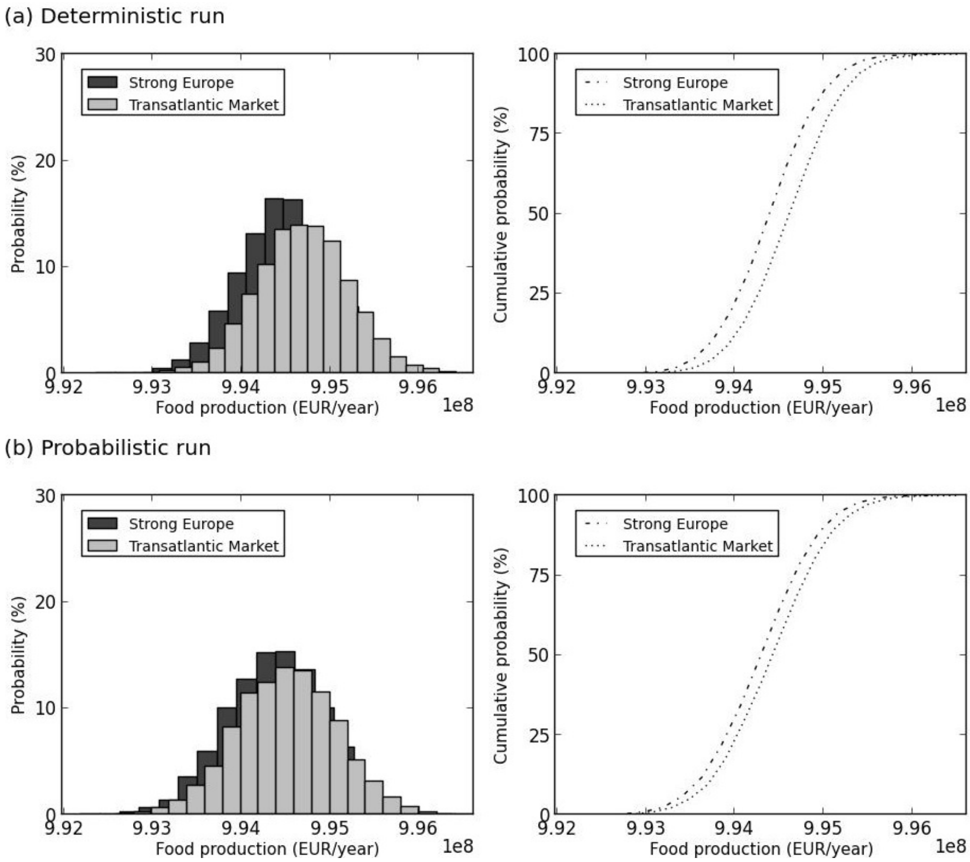


Figure 6.9: Probability distributions (left) and cumulative probability curves (right) representing the probability distributions of regional wood production in the Transatlantic Market scenario and Strong Europe scenarios. The top panels are the results of a deterministic run, the bottom panels the results of a probabilistic run.

6.4 Discussion

6.4.1 Future ecosystem service delivery

In contrast to findings from global ES assessment studies (Costanza et al., 2014), for three out of four services an increase of ES delivery between 2010 and 2050 was found for some scenarios. The increase of ES delivery can be attributed to a lower population growth rate, less demand for agricultural land and an increase of forested areas, trends that are occurring in other developed countries as well (Schröter et al., 2005). These optimistic results, however, need to be interpreted with caution as only a selected set of services has been considered here. While Lawler et al. (2014) predicted a similar increase of ES delivery over time in the United States of America, they also predicted a decrease of biodiversity. As evidence exists that biodiversity positively affects ES delivery (Balvanera et al., 2006), a decline in the delivery of, at least, some services can be expected. Zooming in on individual scenarios confirms this objection. The SE scenario, typified by an increase of managed nature areas, seems to be associated with low ES delivery. Only the GE scenario performs worse. A finding which may be biased by the incompleteness of the set of services considered or a lack of quantified positive effects of specific types of nature management on the considered services. Thus, to obtain reliable results in the future, more services need to be integrated and more data are needed. Not only easily measurable yield gains or losses, but also effects on biodiversity, soil formation, etc. need to be quantified and integrated into the models. A second important element to consider while interpreting these results are the effects of globalisation. While a decrease in agricultural land may increase national ES delivery, it potentially leads to lower ES delivery in other countries (e.g. developing countries). In these countries agricultural production will need to expand to be able to supply the developed countries due to their higher demand for food products compared to their decreasing production (Imhoff et al., 2004). Although calculations were based on the assumption that a service is used sustainably (e.g. wood harvest does not exceeds the forest growth rate), the presented outcomes are not necessarily sustainable. Sustainability largely depends on human consumption and import of ES to fulfil societal demands. However, this is difficult to capture in the local scale models used here. To reveal these aspects, global scale studies are needed.

Most ES-related scenario analyses that have been conducted in the past have focussed predominantly on land cover instead of land use (e.g. Lauf et al., 2014; Maes et al., 2012). In line with Verburg et al. (2009), this study acknowledges the importance of additionally taking into account land use, both in land use change models and ES delivery models. An important incentive to include land use is that changes related to alternative socio-economic development scenarios predominantly exist of management changes, such as, implementations of agro-environmental schemes in agricultural land and conversion from unmanaged to managed nature areas. Accounting only for land cover would have resulted in significant information loss and would have made it harder to distinguish among alternative scenarios based on ES delivery.

6.4.2 The added value of accounting for uncertainties

Taking into account uncertainties may inform decision makers whether a particular scenario robustly delivers more/less services than another one. The analysis shows that, for most services, uncertainties are rather low compared to the differences among scenarios. This indicates that the considered scenarios result in significantly different ES delivery rates. Only for food production uncertainties are sometimes higher than the differences among scenarios.

Although land use change predictions are relatively uncertain, with a mean probability of newly assigned cells between 10 and 70 percent depending on the land use type (Figure 6.5), regional ES delivery is relatively certain. The rather low increase of uncertainty when running the model probabilistically instead of deterministically may have several reasons. First of all, when looking at the individual cells, we see that the uncertainty related to ES delivery is already high in case all inputs are determined deterministically, and that uncertain land use only results in a marginal increase of the uncertainty linked to the ES delivery maps (marginal increase of the cell's PPCI) (Figure 6.8). The uncertainty associated to ES delivery processes clearly overrules the uncertainty associated to land use. While this suggests that the added value of an uncertainty analysis of the predicted land use maps is currently not that high, more data and better insights in ES delivery processes may increase its importance. Besides, as visualised in Figure 6.8, uncertainty propagation seems to become more important at the level of individual cells in case urban expansion rates are high. While this relation is not that pronounced for the services wood production and climate regulation, two services that are predominantly delivered by forests, it becomes more clear for the services that are delivered in areas that are threatened by urban expansion, such as, agricultural land.

Looking at the regional outcomes, the low increase of uncertainties when the model is ran probabilistically instead of deterministically suggests that alternative land use configuration for a particular socio-economic development scenario, obtained through successive runs of the land use change model, all result in similar regional ES delivery rates. This can be explained by the fact that the demand for a particular land use type is driven by the socio-economic scenario which results in a fixed increase/decrease of a particular land use type for each successive run of the land use change model. However, ES delivery does not only depend on land use. Alternative land use configurations may lead to land uses that are allocated on suboptimal soils for the delivery of a particular ES. The findings thus suggest that either ES production is not that sensitive to suboptimal soil types or that the soil suitability indicators used by the land use change model to allocate specific land use types closely correspond to suitability indicators for ES delivery ensuring that in each successive run of the land use change model land use is allocated optimally in terms of ES delivery. For the provisioning services wood production and food production, the second explanation may be valid. Sensitivity to soil type may be high, but soil suitability indicators are comparable. For the regulating services climate regulation and air quality regulation, low sensitivity of ES delivery to changes in soil type may be the reason for the stability of regional ES delivery across successive runs of the land use change model.

6.4.3 Shortcomings

An important limitation of the proposed approach to model future delivery of ES is that only land use change is taken into account while ES delivery may be sensitive to other changes as well. Schröter et al. (2005) denoted climate change as an important factor that may affect ES delivery next to land use change. Unfortunately, up till now, most climate change effects on ES delivery are poorly understood and are therefore hard to include in models for scenario analysis. Davidson and Janssens (2006), for example, reviewed studies on the effect of temperature rise on soil organic carbon storage and found both evidence for positive and negative effects. Another important factor that may influence future ES delivery are potential changes in management practices. Manure application and artificial drainage in Flanders are known to have an effect on soil organic carbon storage (Lettens et al., 2005; Meersmans et al., 2011) and food production (Bollen, 2012). However, no predictions are made on how these factors will change towards 2050. Finally also changes in the composition of the air may influence future ES delivery. Projected decreases of atmospheric PM concentration (Van Steertegem et al., 2009) will lower the value of air quality regulation by vegetation and projected increases of greenhouse gas concentrations will lead to an increase of the value of carbon sequestration in the future (Aertsens et al., 2013). However, the sensitivity analyses of the ES models applied in this study (Table 6.3) clearly identified land use as the most important factor and, therefore, justify the focus on land use change in this study. However, the evidence inserted in the models largely determines the outcome of the sensitivity analyses. The importance of land use can be attributed either to its intrinsic importance or to the vast amount of studies that have focussed on the effects of land use while other important factors, such as, soil type, climate and biodiversity have been studied less.

A second important limitation of the approach applied is that the effect of spatially explicit interactions, such as, neighbourhood effects, distance effects and size effects, could not be taken into account in the BBNs. Integrating these kind of interactions would require additional input nodes representing neighbourhood characteristics (as briefly discussed in chapter 5), a set of BBN models to model ES delivery at several scale levels (Marcot et al., 2001) or connections among models of adjacent grid cells (Giretti et al., 2012). All these practices result in large BBN models that are hard to deal with in terms of compilation time and, therefore, hard to apply on a regional scale. At the moment, only the more advanced GIS-based ES models (e.g. Kareiva et al., 2011) are able to account for some of these spatial interactions. At the other hand, propagating uncertainties, as done in this study, is rather difficult when applying these spatially explicit models.

Not accounting for spatial interactions may also be a reason for the small uncertainty differences between a probabilistic run and a deterministic run. As discussed previously, successive runs of the land use change model will only lead to different land use configurations as the occupied surface of each land use type is more or less fixed. ES models that do not take into account the effects of different spatial configurations will not be able to detect differences among successive runs and will obtain similar total ES delivery rates, resulting in a low increase of uncertainty. Although spatial interactions are not that important for the services considered in this study, for other services, such as, recreation, spatial interactions might be very important. Thus, for these services, uncertainties may increase more in case land use predictions are uncertain instead of deterministic. The same holds for temporal interactions, such as, the influence of land use in 2010 on ES delivery in 2050. As alternative land use configurations may lead to different land use shifts (different combinations of 2010 and 2050 land use), they may lead as well to different delivery rates. Recently, Dallimer et al. (2015) have stressed the importance of such temporal interactions by analysing the effect of historical land use on current service delivery. Again, ES models that do not account for these effects will not be able to detect differences among successive runs. In the current study, temporal effects were only accounted for in the climate regulation model as yearly soil organic carbon storage depends on both the equilibrium organic carbon stock of current land use and the equilibrium organic carbon stock of future land use. However, in this study, no significant increase in uncertainty was found for this service when comparing the deterministic run with the probabilistic run for each scenario.

6.5 Conclusion and recommendations

By coupling a cellular automaton land use change model with BBN models to model ES delivery, future ES delivery for Flanders could be modelled for several plausible socio-economic development scenarios. Although the results suggest that service delivery projections are relatively certain for specific scenarios, large differences among scenarios suggest that future ES delivery is highly uncertain and will depend on realised socio-economic developments. Both decreases and increases of ES delivery were found depending on the scenario and the service considered. As only a limited set of services was taken into account, no optimal scenario can be suggested. To do so, more services need to be included, which will obviously require more data.

Although the applied coupled component model allows uncertainty propagation, the added value of propagating uncertainty related to land use change predictions seems to be low. While ES models are evolving and ES predictions are becoming less uncertain, the importance of land use change uncertainty in these scenario analyses may rise. Besides, accounting for spatially explicit interactions in ES models can also increase the importance of accounting for uncertainties in land use change models.

7 General discussion and conclusions

The main objective of this study was to operationalise the use of Bayesian belief networks to model ecosystem service delivery in Flanders. To attain this aim, the use of Bayesian belief networks to model ecosystem service delivery was tested for a local and a regional study and for a range of applications: decision support, prediction, system exploration, and projecting future ES delivery. In this chapter, the main achievements of this study will be highlighted and, based on the study's main findings, the potential of the modelling approach for ecosystem service modelling will be reviewed. This chapter ends with several recommendations for future research, focussing both on ecosystem services research in Flanders and, more specifically, on the future of Bayesian belief networks in this context.

7.1 Main achievements

7.1.1 Knowledge integration

This study illustrates an approach to integrate current knowledge on ES delivery in Flanders while being able to incorporate uncertainties attached to this knowledge. Previous attempts to integrate available knowledge all faced the challenge of dealing with uncertainty and variability. The use of two model parameterisations, one to predict a high estimate and one to predict a low estimate of ES delivery, has been put forward as a potential solution to reveal the full range of possible ES delivery rates (e.g. Broekx et al., 2013b). However, applying this approach leads to a considerable loss of information. The information content and, hence, the decision support capacity of a low and a high estimates is considerably lower than that of a probability distribution between this low and high value. The integration of knowledge into a cause-effect framework entails some additional advantages over existing approaches. Explicit representation of the integrated knowledge as causal relations in a graphical network opens ways to new forms of model application. The developed models can be used, for example, to help stakeholders understand the delivery processes of ES (Voinov and Bousquet, 2010), as a basis for discussions among scientists form different disciplines or to enhance model acceptance by transparently visualising the followed approach (Jakeman et al., 2006). On top, it may facilitate model evaluation by external experts. Aside from the graphical component, explicitly considering causal relations within ES delivery processes and in between the delivery processes of multiple services leads to additional insights on interactions among services and drivers that cause these interactions. Compared to previously applied approaches to identify interactions based on pairwise comparison of ES delivery maps (e.g. Schneiders et al., 2012), the proposed approach based on joint probability distributions is less 'black-box' and provides additional insights in factors that drive these interactions.

7.1.2 Local and regional decision support

In this study, BBNs have been operationalised for a range of applications: decision support under uncertainty (chapter 3), system exploration (chapter 4), prediction (chapter 5) and projecting (chapter 6). Although this study demonstrates the opportunities of BBNs for all these applications, decision support under uncertainty can be seen as the main aim of all chapters. While chapter 3 discusses an application of BBNs to support local decision making, chapter 4, 5 and 6 focus on decision support at the regional level. The chapters point at differences between the operationalisation of BBNs for regional and local decision support. For local case studies, a single model is enough for decision support as management alternatives have a direct effect on the input nodes of the model and can be readily integrated in the model. Using a Bayesian decision network approach, management alternatives can be easily evaluated and compared. Due to the well-defined object, a freshwater pond of one hectare, the model operated on, a lumped non-spatial model was sufficient. At the regional level, the effect of decision making on ES delivery is more complex as spatial aspects need to be taken into account. Regional decision making will predominantly affect ES delivery through its effect on regional land use allocation. To achieve similar recommendation for decision makers as in chapter 3, BBNs need to be developed spatially and need to be coupled with a land use change model. This way, different alternatives (expressed as socio-economic development scenarios) can be evaluated taking into account both land use change uncertainty and ES delivery uncertainty.

7.1.3 Bayesian belief networks for mapping uncertainties

The ability of BBNs to account for uncertainties is especially useful in a mapping context. Because ES mapping is generally based on a limited set of input maps, especially at the European and at the global scale (e.g. Maes et al., 2012), mapping attempts are characterised by high uncertainty. Spatial mapping of BBN predictions, however, has been a challenging task for different reasons: (1) inference algorithms are time-consuming hampering pixel-based application of BBNs, (2) no user-friendly ways exist to couple GIS software and BBN software and (3) spatial visualisation of uncertainties is challenging. In this study, a QGIS plug-in has been developed to link BBN software and GIS software, a tool that might be useful in several research domains that deal with spatial data and uncertainties. The calculation speed challenge was solved through converting the model into a look-up table prior to applying the model on spatial input data. This conversion speeded up the assignment of model predictions to individual pixels considerably. To map the uncertainty attached to the model predictions, several ways of visualising uncertainties were proposed and incorporated as options in the plug-in. Although the capacity of these uncertainty representations to support decision making has been studied (e.g. Deitrick and Edsall, 2006; MacEachren et al., 2005; Kubícek and Sasinka, 2011), their applicability in the ES research domain still needs to be investigated.

7.2 The Bayesian belief network approach revisited

7.2.1 The influence of scale

By developing a model to assess ES delivery of a specific ecosystem and a model for regional ES assessment, this study has illustrated the influence of scale on model development. First of all, there is a difference in the way ES delivery processes are included. For some ecosystems, such as the ponds considered in chapter 3, data are extensively available and system understanding is high. This allows the development of networks that consider processes more in detail (e.g. including the abundance of specific groups of organisms as network nodes). This, in turn, allows that more detailed management practices can be evaluated by using the model. However, the more in detail a process is being modelled, the more the inability of BBNs to include feedback loops will become a limitation. As regional models need to be generally applicable across a region, they may not be overfitted to a specific ecosystem by including detailed processes based on local knowledge and data. As a result, processes will be modelled less in detail. This also entails that different data sources are being used in both situations. At the regional level, knowledge sources will be limited to regional maps, meta-analyses and expert knowledge. For local case studies, empirical data and local expert knowledge will be more important. However, due to obliged discretisation which leads to information loss, BBN models are less suitable to deal with continuous empirical data compared to other modelling techniques. Although the review in chapter 2 has shown that local and regional BBN applications are equally represented in the literature, BBNs seem to be more suited for large scale studies, mainly because of their limited capacity to deal with feedback loops and empirical data. In case no or only a limited amount of data are available, BBNs can be useful as well in for local case studies.

7.2.2 Certainty of uncertainty

Knowledge on uncertainties is extremely useful for decision support as it may, for example, determine whether differences between the outcomes of two alternative management practices are significant. Thus, knowledge on uncertainty may lead to more robust decisions. Although BBNs allow the incorporation of uncertainties, our knowledge on uncertainties is often incomplete, especially in the ES research domain. Generally, only a small fraction of the full spectrum of uncertainties is taken into account (For a complete overview of possible sources of uncertainty, see

Ascough et al. (2008)). The uncertainty attached to BBN outputs must, therefore, be interpreted as the part of uncertainty we are aware of or, in other words, as a lower bound of the true uncertainty. This lower bound is enough to conclude that two outcomes are not significantly different, however, not to conclude the opposite in case significant differences are found based on the model output.

7.2.3 Integration of models

By coupling BBNs to other models and software packages, as has been done in this thesis and in other studies in the past (e.g. Farmani et al., 2009; Kocabas and Dragicevic, 2007), the benefits of BBNs can be combined with the benefits of other models. This also helps to overcome the shortcomings encountered while modelling with BBNs. An important shortcoming of BBNs that has been mentioned several times in this work is the inability of BBNs to model spatial and dynamic processes. Model coupling can offer a solution here. In chapter 6, for example, a cellular automaton was used to model the dynamic process of land use change, while BBNs were used to deal with the uncertainty associated to the predicted land use change and the uncertainty associated to ES delivery. Similarly, Kocabas and Dragicevic (2007) applied BBNs to introduce probabilistic transition rules in a cellular automaton to model land use change. Thus, BBNs can also complement other models in case parts of the processes that are being modelled are poorly understood and highly uncertain. In the context of ES modelling, especially the links between functions and values are still highly uncertain, mainly due to the diversity of valuation methods being used and the diversity of social contexts and stakeholders to consider. In contrast, relations between biophysical characteristics of ecosystems, at the one hand, and the provisioning of ecosystem functions, on the other hand, are being more and more understood due to monitoring and modelling. Coupling process-based ecological models with BBNs might be a promising technique to model the full cascade of ES delivery in the future.

Also to improve the exploration of BBN model results, model coupling might offer solutions. Before, Bayesian decision networks have been used to determine optimal management practices based on one objective, being the expected value of one output node (e.g. Dorner et al., 2007) or the expected value of several output nodes (e.g. Kragt et al., 2011; Barton et al., 2008). However, as illustrated in chapter 3, other aspects such as the uncertainty of an outcome might determine the desirability of a particular management decision. To deal with this variety of objectives, more sophisticated optimisation algorithms are needed. Genetic algorithms (Mitchell, 1996) can, for example, be used to infer optimal management decisions which can be defined as combinations of states of the model's input nodes, i.e. the population of candidate solutions in the genetic algorithm. Based on a complex objective function that takes into account the expected value of one or more output nodes in combination with the associated uncertainties, optimal combinations of input node states (management decisions) can be found (Farmani et al., 2009).

7.2.4 Integrating expert and stakeholder knowledge

As discussed in the previous section BBNs are promising to model the most uncertain links in the ES cascade. The use of stakeholder knowledge should focus on these aspects as well. However, stakeholders should also be consulted in the initial stage of the model development process to set up the boundaries: what are realistic management practices that need to be investigated and what are the services that need to be taken into account. Next, based on existing studies, data and expert judgements, the modeller can initiate the model development process. This preliminary model can be discussed with stakeholders to review the model and to suggest improvements. A similar methodology was applied to construct the model presented in chapter 3. As a final step, stakeholders can be consulted to determine and quantify the links between ecosystem functions and benefits. This final step can be followed as an alternative for monetary valuation or to complement monetary valuation. Although the transparency of BBNs facilitates stakeholder engagement, up till now, only a limited number of BBN studies have chosen for this alternative valuation approach (Van der Biest et al., 2014).

7.2.5 Shortcomings of Bayesian belief networks

As mentioned previously, the completeness of the network model will determine whether its predictions are realistic and whether it identifies drivers and interactions correctly. Although an expansion of the network structure would be necessary to go towards a more complete network, standard desktop computer systems are not able to handle such large networks. The time needed for belief updating in BBNs grows exponentially with the number of nodes (Jensen and Nielsen, 2007), a problem typically referred to as NP-hard in theoretical computer science (Cooper, 1987). Also memory usage increases drastically for complex networks. Belief updating with the network presented in chapter 4 consumes, for example, already more than two gigabytes of rapidly accessible memory (random-access memory or RAM) which is already too much for 32bit software and close to the maximum for 64bit software ran on standard hardware. Although more efficient network structures exist that require less memory and time for belief updating, most problems can't be represented by such simplified structures. The use of approximate belief updating algorithms might be a solution in case the availability of memory is a limiting factor. However, approximate belief updating is more time consuming than exact belief updating. A more convenient solution would be to expand the available RAM of your computer system. Although network size will remain a restricting factor, working with slightly larger networks will become possible by expanding the available RAM.

Nevertheless, incompleteness of the set of considered services will remain an important issue to consider when developing a BBN and analysing its results, especially in case models are used to optimise management. Potential unintended effects of considering an incomplete set of services have been illustrated in chapter 3. To minimise biases resulting from incomplete sets of ES, services need to be selected carefully. This selection will predominantly depend on the aim and content of the study. To ensure that all relevant services are taken into account, stakeholders need to be consulted. Including biodiversity status as an extra output node might be a solution to account for services that were not explicitly considered as output nodes in the model. Avoiding biodiversity loss can be set as a boundary condition for the optimisation of management practices. Such calculations, performed conditionally on a specific event or restriction, are common practice for BBNs. A similar boundary setting approach might be used as well to account for sustainability issues, for example, by setting sustainable use as a boundary condition. For these applications, explicitly defining sustainable use will be a challenge.

Another shortcoming of a BBN approach to model ES delivery is the limited capacity to take into account spatial interactions. Not taking into account these spatial interactions might lead to wrong predictions for some services (Syrbe and Walz, 2012). To model recreational use, for example, not considering spatial interactions, such as, travel distance to populated centres might lead to overestimating the recreational use value of a pixel in case it's located far from populated centres (Bateman et al., 1999). Also to identify interactions among services, spatial interactions might be important. The approach proposed in chapter 4 only considered on-site interactions among services which might differ from off-site interactions. Food production, for example, excludes the production of wood on the same site. However, there might be a synergy at a larger spatial extent as forests may, for example, serve as wind shelters for adjacent agricultural fields. Although model structures have been proposed to include spatial interactions into a BBN framework (Giretti et al., 2012), the amount of nodes required to make these networks operational impedes belief updating in a reasonable timespan. The use of landscape metrics (Frank et al., 2012) as input nodes of a BBN can be a work-around to account for some of the occurring spatial interactions.

7.3 Future research on Bayesian belief networks

7.3.1 Ecosystem service modelling

Although BBN modelling might look like a promising technique based on the cases presented in this study, they are only suitable to model a limited set of services. For many services, production processes need to be simplified considerably to be able to model them with BBNs. If more data becomes available and processes are better understood, sticking to these simplified models might not be the way to move forward in science. More complex models will be needed to analyse and operationalise this data. This statement suggests that future data collection will not favour the use of BBNs. This is, however, not entirely true. It is true that there are a lot of alternative modelling techniques available to deal with continuous empirical data and that they frequently outperform BBNs in predictive performance (e.g. Ordóñez Galán et al., 2009). However, as already discussed in section 7.2.3, BBNs will remain useful to model those links in the ES cascade that are highly uncertain. To model these links, expert and stakeholder knowledge will be needed, data that is frequently not continuous (e.g. linguistic expert knowledge) and often uncertain, two data characteristics that favour the use of BBNs. Moreover, BBNs can still add value to large extent ES assessment, such as, ES assessments at the scale of Europe. On this scale level, detailed data won't become available soon and BBNs might be one of the best models available to objectively deal with this data scarcity, by accounting for the high variability in ES delivery that arises from using less detailed land use and soil maps and by communicating these uncertainties. The same holds for services for which collection of empirical data is not possible and modellers need to rely only on expert judgement. On top, BBNs can be useful in some specific cases, for example, as illustrated in this study, to entangle the causal relations among the production processes of a limited set of services, based on currently available data (chapter 4) and to develop specific decision support tools to inform people on risks by means of probabilities (chapter 3).

7.3.2 Model validation and implementation

As discussed above, future applications of BBNs are likely to stay predominantly expert-based. Therefore, model validation will become very important to ensure the credibility of the models in the future (Marcot, 2012). Although a lot of validation approaches exist, expert-based validation is currently the most popular technique (chapter 2). Although model evaluation based on experts and stakeholders can yield interesting new insights, it is frequently contested due to its subjective nature (Refsgaard et al., 2007; Jakeman et al., 2006). Thorough model validation is, however, a challenge that most ES models, that are currently being used, are facing. On the other hand, also purely data-driven evaluation is not always the desired solution to define a model's performance. In some cases, model performance is not defined by its predictive performance, but by the effects it has on the community and the decisions they make (Voinov and Bousquet, 2010). More studies need to focus on the interactions between models and stakeholders, especially in the field of ES modelling, a domain that explicitly deals with the interests of stakeholders. This might again favour the use of BBNs because of their high transparency. Confronting stakeholders with the models and outcomes presented in this study might be a first step towards evaluating the performance of the models presented in this study. Using the predicted probability distributions as such to support decision making might be more difficult. For this purpose, model predictions need to be framed properly regarding the uncertainties that were accounted for, the services that were included and the processes that were considered. For rather simple decision making problems (e.g. medical diagnosis modelling), this be can be easily done, ensuring that predicted probability distributions can be used to guide decision making. For ES models such as the ones presented in this work, framing the results is far more complex, explaining why BBN models themselves rather than their predictions are currently being used to guide decision making.

7.3.3 Remaining challenges

An important challenge that still needs to be resolved if we want to employ BBNs at their full potential is related to the dependencies that exist among individual predictions of a BBN model. To give an example, a BBN model's prediction for food production of cropland and grassland will be highly dependent. Knowing that food production under the cropland scenario will be high will influence our belief on food production under the grassland scenario as we assume a good soil quality based on this newly acquired knowledge. As illustrated in this example, dependencies hamper direct comparison of the outcome of two alternative management practices and make it, for example, hard to answer highly relevant questions, such as, 'What is the chance that ES delivery associated to management practice A is higher than ES delivery associated to management practice B?'. These dependencies, moreover, make that upscaling the uncertainty of individual pixel values to an estimate of the uncertainty associated to total regional ES delivery can be far more complex than the simplified approach proposed in chapter 5 and 6. More research on dealing with these dependencies is necessary to accurately compare alternative management practices and to obtain accurate estimates of the uncertainty associated to total regional ES delivery.

7.4 Future research on ecosystem services in Flanders

7.4.1 Redirecting the research focus

In recent years, a lot of effort has been invested into integrating knowledge on ES delivery. In Flanders, several research projects (e.g. Nature Value Explorer (Broekx et al., 2013b), ECOFRESH (Van der Biest et al., 2013), ECOPLAN) have contributed to attaining this aim, mainly through analysing and merging existing studies, technical reports and scientific publications. Also this study has focussed predominantly on knowledge integration. The focus on knowledge integration and on converting this knowledge into operational tools has been largely driven by the urgent need for ES assessment tools to inform spatial planning decisions. Also the EU biodiversity strategy has been a driver in Europe for orienting research towards operational tools (Maes et al., 2012). However, a lot of knowledge gaps exist and research efforts will need to shift from knowledge integration to identifying knowledge gaps and, eventually, to addressing these knowledge gaps. While it is not likely nor efficient that ES scientists start studying these knowledge gaps themselves, enhanced communication among ES scientist and experts in the field, researchers that have been studying ES delivery processes decades before the concept was born, may lead to new research subjects and, eventually, new insights that are currently needed to make decisions based on ES delivery more robust.

One of the knowledge gaps encountered in this study is the absence of (applicable) knowledge on the relation between biodiversity and ES supply. Although evidence is available that these relations are positive (Balvanera et al., 2006), many models do not take them into account. As a result, ES delivery is frequently underestimated for nature-oriented management practices (e.g. implementation of agro-environmental schemes) and land use types (e.g. heathland). Due to this bias, applying ES models might lead to management suggestions that are counter-productive to protect ecosystems and biodiversity, the main aim of the introduction of the ES concept. Clearly, the effects of biodiversity on ES delivery need to be studied more in depth.

7.4.2 Implementation in decision support

Although being a hot topic in scientific literature, practical use of the ES concept and associated prediction models in Flanders is still limited to a few case studies (Broekx et al., 2013b). From the five potential application domains mentioned by Gómez-Baggethun and Barton (2013), the concept has only been extensively used used for awareness raising and accounting. The use of the concept for priority setting, instrument design and litigation is still very limited. One reason for this might be the complexity of decision making processes that involve ES. These decision making processes, generally related to land management and land conversion, are complicated due to a range of juridical, economic, ecological and social restrictions which have to be dealt with. Although the ES concept definitely has the potential to facilitate these processes by balancing ecological, economic and social needs, clear and practical suggestions on how to implement the concept are still lacking. Although a broad range of 'easy to use' models and tools are being developed to facilitate the implementation of the concept, lacking information on the validity of their results and associated uncertainties is threatening their credibility (Jacobs et al., 2014).

Another option might be the use of more complex models that model ES delivery with a high level of detail, models that are generally trusted more by end-users. However, end-users generally need to invest a lot of time and money to implement these models in their daily decision making. For effective decision support, model outputs and potential ways to query model results need to be tailored to the needs of end-users according to the what-if questions of interest. Simple models, on the other hand, are far more easy to implement but are often not detailed enough to support end-users' decisions. The use of simple models such as BBNs that do report uncertainties and that are easy to adapt according to the needs of end-users might be a solution for both issues mentioned above. Moreover, their high model transparency may strengthen end-users' trust and may support engagement of end-users.

This engagement of end-users during model development is reported as a crucial factor that determines successful adoption of models (McIntosh et al., 2011). This engagement ensures that models are designed to meet end-users' needs and that models are trusted by the end-users. As discussed in Chapter 2 and demonstrated by several academic studies (e.g. Zorrilla et al., 2010), BBNs are suitable models for participatory model development. Whether BBNs are also able to affect real-life decision making still needs to be demonstrated.

Appendix A

To quantify the conditional probability tables of a Bayesian belief network, a range of data types can be used. Different data sources and data types, with often different interpretations of uncertainty, require different protocols to convert them into conditional probability tables. The protocols applied in this study are discussed in detail below.

A.1 Expert knowledge

A broad range of methods exist to integrate expert knowledge into BBNs (Kuhnert et al., 2010). In this study, both elicitation of complete conditional probability distributions (chapter 3) and elicitation of quantitative estimates (chapter 4) were chosen as elicitation techniques. Elicitation of complete probability distributions was carried out through an online questionnaire. To facilitate the questionnaire, conditional probability distributions were elicited with a resolution of 25%. While this reduced the set of possible distributions drastically, filling out the survey remained a cognitive demanding task for the experts involved. An example question from the questionnaire is provided below.

Question 1. Given the fish densities provided below, what level of water turbidity do you expect? Colour exactly four bullets on each row and divide them between the suggested states according to your belief.

	Water turbidity	
Fish density	Low (<100 mg/L)	High (>100 mg/L)
Zero (0 kg/ha)	OOOO	OOOO
Low (0-200 kg/ha)	OOOO	OOOO
Average (200-500 kg/ha)	OOOO	OOOO
High (500-1000 kg/ha)	OOOO	OOOO

In case a lot of probability distributions need to be defined and in case relations for which CPTs need to be defined are less tangible, finding qualified experts may be hard. Hence, other approaches were used to populate the CPTs of the regional ES models with expert knowledge. Instead of conditional probability distributions, experts frequently provide quantitative estimates, such as, those provided in expert-based scoring studies (Burkhard et al., 2009). It was this kind of expert knowledge that was extracted from scientific publications and technical reports to populate some of the CPTs of the regional ES models. A downside of this approach is that information on the uncertainty associated to this expert knowledge is not available. Therefore, CPTs based on expert knowledge needed to be populated deterministically in the regional models.

A.2 Regression models

Regression models, reported in scientific publications and technological reports, can be directly implemented in a BBN as an equation that calculates the value of a child node (response variable of the regression model) based on the value of its parent nodes (predictor variables of the regression model). Netica, the applied software package to develop BBNs, transforms this equation into CPTs by sampling a range of possible parent node values and by calculating the outcome for each sample. Although all nodes in a BBN are defined as discrete variables, the sampling process occurs continuously. This way, a probability distribution instead of a single value is obtained for each row of the CPT or for each combination of the parent nodes' states. The more samples are taken, the better this distribution approximates reality. In this study, a fixed number of 1000 samples, as a balance between accuracy and calculation time, was used to convert equations into CPTs.

This approach, however, does not account for the uncertainties associated to the estimated coefficients of the regression model. If these are reported as well, the regression model can be converted into CPTs via a Monte Carlo simulation, by assuming, for example, that the estimated coefficients are normally distributed. In this Monte Carlo simulation, both the predictor variables (similar to the approach described above) and the coefficients need to be sampled. The obtained CPT accounts for both the uncertainty associated to the discretisation process and the uncertainty associated to the predicted regression model.

Dataset:

Soil texture	Drainage Class	Land use
Z	a	Forest
Z	a	Forest
S	b	Grassland
Z	a	Heathland

Counting

CPT:

		Land use			
Soil texture	Drainageclass	Forest	Heathland	Cropland	Grassland
Z	a	2/3	1/3	0	0
…	…	…	…	…	…
S	b	0	0	0	1
…	…	…	…	…	…

Figure A.1: An illustration of the counting algorithm for a small dataset with four records.

A.3 Empirical data

In case empirical data were available, they were used to learn those CPTs for which the data contained all necessary information. The applied learning algorithm depends on the characteristics of the dataset. In case the dataset was complete with no missing values, CPTs were learned through counting of records (Figure A.1).

If the dataset contains incomplete records, CPTs were learned using the expectation-maximisation algorithm, a frequently applied learning algorithm in the literature which generally yields robust results (Norsys Software Corporation, 1998). This algorithm repeatedly carries out an expectation step followed by a maximisation step until the increase of model fit levels off. In the expectation step, incomplete records are completed by running the model that was obtained by the previous maximisation step. Subsequently the loglikelihood of the model (LL(model|data)) is calculated to evaluate the model's fit. If no prior knowledge on the model's CPTs is available, the loglikelihood can be simplified to the sum of the logarithm of P(record|model) for all records in the dataset. During the maximisation step, the algorithm will update the model's CPTs to maximise its loglikelihood. As the expectation step created an artificial complete dataset, the model's CPTs can be updated through counting (Jensen and Nielsen, 2007).

Both methods, that are essentially frequentist approaches, are not ideal for model learning based on small or sparse datasets. For example, the CPT, shown in Figure A.1, assigns a probability of zero to the occurrence of grassland on a sandy dry soil

(Za.), a finding that does not reflect reality, but is a result of the rather small dataset that was used to learn the model. For such datasets, Bayesian estimation is more appropriate. First, CPTs need to be defined based on prior knowledge (based on expert knowledge or literature). Next, the data is used to update these preliminary CPTs. This way, outcomes that were not recorded in the dataset will not receive a probability of occurrence equal to zero. A Bayesian learning algorithm will only lower the prior probability for this outcome. Similarly, by using prior knowledge, the model's prediction will not be indifferent for an event that was not recorded in the dataset. Similar algorithms as those applied by counting and EM-learning can be used for Bayesian estimation. As the datasets employed in this study are all complete and rather large, only parameter estimation through counting was applied.

An important aspect that needs to be accounted for prior to model learning is the correctness of the graph. In contrast to other information sources, such as regression models, a dataset does not suggests a particular structure of the network. Therefore, checking whether all dependencies and independencies are encoded properly in the graph is necessary before CPTs are being learned.

A.4 Key figures

Key figures, reported in scientific publications and technical reports, are one of the most popular data sources in ES modelling studies. Mainly because of the ease of applying them. Key figures are especially popular in studies that focus predominantly on the monetary value of ES delivery. These studies apply key figures, that quantify ES delivery per unit area of a specific land cover, to assess regional ES delivery (e.g. Costanza et al., 1997). Although key figures are frequently reported together with a standard deviation or as ranges instead of single values, up till now, most studies that apply key figures have interpreted them as fixed values.

An important advantage of using key figures in a BBN framework is that uncertainties can be taken into account. In this study, reported ranges are translated into uniform distributions, while reported values for the mean and standard deviation are converted into normal distributions that are fitted to these values. Both distributions are subsequently discretised to fit into the model's CPTs. For a visualisation of this process, see Figure A.2.

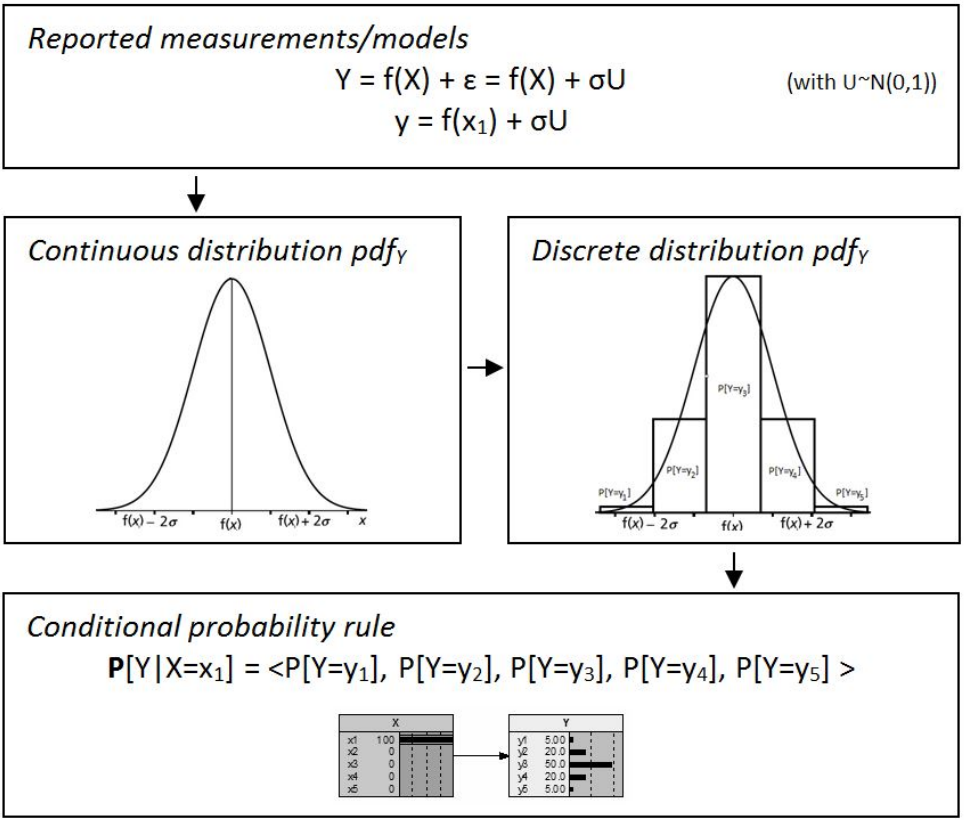


Figure A.2: Visual representation of the followed procedure to convert reported key figures into conditional probability tables.

Appendix B

Table B.1: An overview of the model's variables and dependencies.

Submodel	Node name	Code	Parent nodes
Management	Management Scenarios	MSc	
	Management Costs	MC	MSc, AF, FS__pl, FS__pi, FS__b
Fish production	Additional Feeding	AF	Msc
	Fish Stocking Planktivores	FS__pl	Msc
	Fish Stocking Piscivores	FS__pi	Msc
	Fish Stocking Benthivores	FS__b	Msc
	Fish Produced Planktivores	FP__pl	FS__pl, AF
	Fish Produces Piscivores	FP__pi	FS__pi
	Fish Produced Benthivores	FP__b	FS__b, AF
	Fish Produced Net Gain	FPNG	FS__pl, FS__pi, FS__b, FP__pl, FP__pi, FP__b
	Value Produced Fish	VPF	FP__b, FP__pl, FP__pi
Nitrogen retention	Retention Time	RT	
	Water Depth	WD	
	Purification	P	
	Catchment Land Use	LU	
	Nutrient Load In	NLI	LU
	Denitrification	D	WD, RT
	Nutrient Load Out	NLO	NC, D
	Nutrient Concentration	NC	AF, NLI, P
	NChange	NCh	NLI, NLO, WD, RTI
	Avoided Abatement Cost	AAC	
	Value N Change	VNC	AAC, NCh
Cultural services	Shoreline Complexity	SC	MSc
	Accessibility	A	Msc
	Density Large Zooplankton	DLZ	FP__pl
	Density Phytoplankton	DP	DLZ, NC
	Water Turbidity	Wtu	FP__b
	Water Transparency	WTr	Wtu, DP
	Cyanobacteria	C	NC
	Water Quality	WQ	C, DP
	Presence Of Macrophytes	POM	WD, WT
	Species Richness	SR	POM, SC
	Water Quality and Transparency	WQT	WQ, WT
	Willingness-to-pay	WTP	WQT, SR, A, SC
	Total Economic Value	TEV	MC, VNC, WTP, VPF

Appendix C

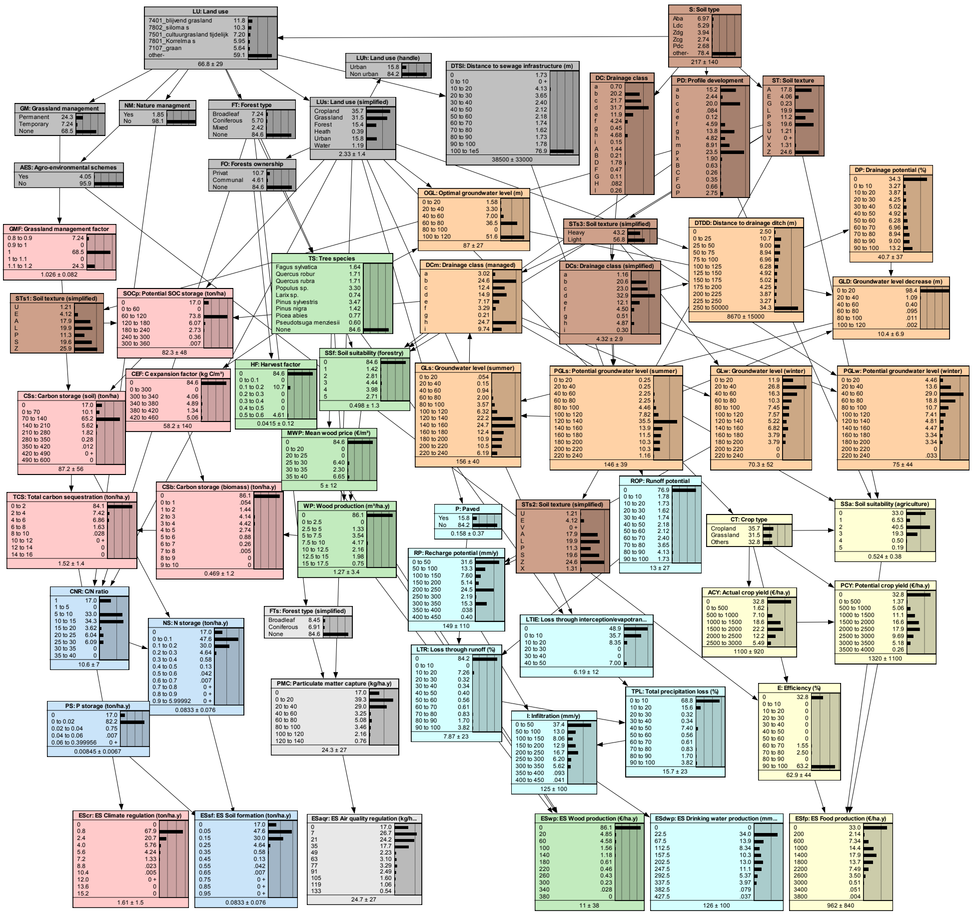


Figure C.1: Bayesian belief network for regional ecosystem service assessment.

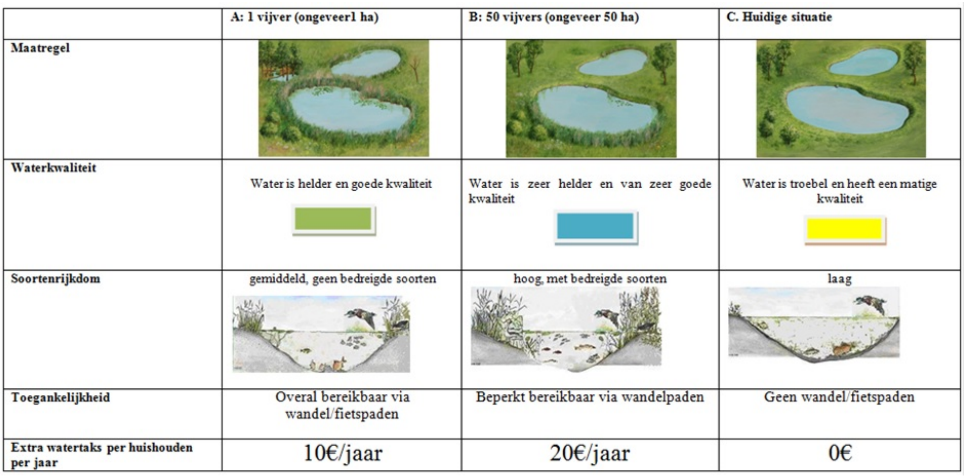
Table C.1: Detailed information on the network's nodes and the applied equations and knowledge bases to populate the model's CPTs. The states of discretised variables are represented as [lower bound:step size:upper bound].

Submodel	Node name	Code	States**	Parent nodes	Equation*	References
Input nodes	Land use	LU	117 land use classes			Poelmans and Van Daele (2014); AGIV (2001)
	Soil type	S	417 soil types			AGIV (2001)
	Distance to sewage infrastructure(m)	DTSI	[0:10:100]	LU		Poelmans and Van Daele (2014); VMM (2015)
	Distance to drainage ditch (m)	DTDD	[0:10:100]	LUs,DC		Poelmans and Van Daele (2014); AGIV (2001); Staes (2014)
Land use	Grassland management	GM	Permanent, Temporary, None	LU		
	Nature management	NM	Yes, No	LU		
	Forest type	FT	Broadleaf, Coniferous, Mixed, None	LU		
	Land use (simplified)	LUs	Cropland, Grassland, Forest, Heath, Urban, Water	LU		
	Agro-environmental schemes	AES	Nature, Environmental, None	LU		Statistics Belgium (2012)
	Forest ownership	FO	Privat, Communal, None	LUs1		Afdeling Bos & Groen (2001)
Soil type	Soil texture	ST	A,E,G,L,P,S,U,V,X,Z	S		Van Ranst and Sys (2000)
	Drainage class	DC	a,b,c,d,e,f,g,h,i,A,B,D,F,G,I	S		Van Ranst and Sys (2000)
	Profile development	PD	a,b,c,d,e,f,g,h,m,p,x,B,C,F,G,P	S		Van Ranst and Sys (2000)
Drainage management	Soil texture (simplified)	STs3	Heavy, Light	ST		Van Ranst and Sys (2000)
	Drainage class (simplified)	DCs	a,b,c,d,e,f,g,h,i	DC		
	Drainage class (managed)	DCm	a,b,c,d,e,f,g,h,i	STs3,GLs		
	Drainage potential (%)	DP	[0:10:100]	DTDD	(1-DTDD/250)*100	
	Optimal groundwater level (m)	OGL	[0:120:20]	LUs,TS		Staes (2014)
	Groundwater level decrease (m)	GLD	[0:120:20]	DP,OGL,PGLs	(DP/100)*(OGL-PGLs)	
	Potential groundwater level (summer) (m)	PGLs	[0:20:240]	DCs,STs3		Liekens et al. (2013b)
	Potential groundwater level (winter) (m)	PGLw	[0:20:240]	DCs,STs3		Liekens et al. (2013b)
	Groundwater level (summer) (m)	GLs	[0:20:240]	GLD,PGLs	GLD+PGLs	
	Groundwater level (winter) (m)	GLw	[0:20:240]	DCm,STs3		Liekens et al. (2013b)
Climate regulation	Soil texture (simplified)	STs1	U,E,A,L,P,S,Z	ST		
	Potential SOC storage (ton.ha^{-1})	SOCp	[0:60:360]	STs1,DCm,Lus		Meersmans et al. (2008)
	Grassland management factor	GMF	[0.8:0.1:1.2]	GM		Van Cleemput et al. (2007)
	Carbon storage (soil) (ton.ha.y^{-1})	CSs	[0:70:490]	SOCp,GMF	SOCp*GMF	

	C expansion factor (kg $C.m^{-3}$)	CEF	[300:40:460]	TS		Van de Walle et al. (2005)
	Carbon storage (biomass) ($ton.ha^{-1}.y^{-1}$)	CSb	[0:1:10]	CEF,WP	CEF*WP	
	Total carbon sequestration ($ton.ha^{-1}.y^{-1}$)	TCS	[0:2:16]	CSb,CSs	CSb+CSs*0.01	
	ES Climate regulation ($ton.ha^{-1}.y^{-1}$)	EScr	[0:1.6:16]	TCS	TCS	
Air quality regulation	Forest type (simplified)	FTs	Broadleaf, Coniferous, None	FT		
	Particulate matter capture ($kg.ha^{-1}.y^{-1}$)	PMC	[0:20:140]	FTs,LUs1		Tiwary et al. (2009); Nowak et al. (2006); Oosterbaan and Kiers (2011); Oosterbaan et al. (2006)
	ES Air quality regulation ($kg.ha^{-1}.y^{-1}$)	ESaqr	[0:14:140]	PMC	PMC	
Soil formation	C/N ratio	CNR	[0:5:40]	LUs1,FT,NM		Liekens et al. (2013b)
	N storage ($ton.ha^{-1}.y^{-1}$)	NS	[0:0.1:1]	CNR,CSs	CSs*0.01/CNR	
	P storage ($ton.ha^{-1}.y^{-1}$)	PS	[0:0.02:0.08]	NS	NS/15	Koerselman and Meuleman (2015)
	ES Soil formation ($ton.ha^{-1}.y^{-1}$)	ESsf	[0:0.1:1]	NS,PS	NS+PS	
Drinking water production	Paved	P	Yes,No	LU		Poelmans and Van Daele (2014)
	Runoff potential (%)	ROP	[0:10:100]	DTSI	(1-DTS/100)*100	
	Soil texture (simplified)	STs2	U,E,V,A,L,P,S,Z,X	ST		
	Recharge potential ($mm.y^{-1}$)	RP	[0:50:450]	GLw,STs2		Batelaan and De Smedt (2007)
	Loss through runoff (%)	LTR	[0:10:100]	P,DTSI	P*((100*(100-DTS)/100) + 10)	
	Loss through evapotranspiration (%)	LTIE	[0:10:50]	TS,LUs1		Staes (2014)
	Total precipitation loss (%)	TPL	[0:10:100]	LTR,LTIE	max(LTR,LTIE)	
	Infiltration ($mm.y^{-1}$)	I	[0:50:450]	RP,TPL	RP*(1-TPL/100)	
	ES drinking water production ($mm.y^{-1}$)	ESdwp	[0:45:450]	I	I	
Wood production	Tree species	TS	Fagus sylvatica, Quercus robur,, Quercus rubra, Populus sp., Larix, sp., Pinus sylvestris, Pinus nigra, Picea abies, Pseudotsuga menziesii, None	LU,FT		
	Harvest factor	HF	[0:0.1:0.6]	FO		Liekens et al. (2013b)
	Soil suitability (forestry)	SSf	0,1,2,3,4,5	TS,ST,PD,DCm		De Vos (2000)
	Mean wood price (€.m^{-3})	MWP	[20:5:40]	TS		Demey et al. (2013)
	Wood production ($m^3.ha^{-1}.y^{-1}$)	WP	[0:2.5:17.5]	SSf,TS		Moonen et al. (2011); Jansen et al. (1996)
	ES Wood production (€.$ha^{-1}.y^{-1}$)	ESwp	[0:40:400]	MWP,WP,FO	MWP*WP*FO	

Food production	Crop type	CT	Cropland, Grassland, Others	Lus		Poelmans and Van Daele (2014)
	Soil suitability (agriculture)	SSa	0,1,2,3,4,5	CT,ST,PD,DCm		Bollen (2012)
	Actual crop yield (€.ha^{-1}.y^{-1})	ACY	[0:500:3000]	LUs		Van Broekhoven et al. (2012)
	Potential crop yield (€.ha^{-1}.y^{-1})	PCY	[0:500:4000]	ACY,CT		AGIV (2001); Bollen (2012)
	Efficiency (%)	E	[0:10:100]	CT,AES		Van Gossum et al. (2014, 2012); Reubens et al. (2010); Van Zeebroeck and Maertens (2009)
	ES Food production (€.ha^{-1}.y^{-1})	ESfp	[0:400:4000]	PCY,SSa,E	PCY*Ssa*E	

Appendix D



	A: 1 vijver (ongeveer1 ha)	B: 50 vijvers (ongeveer 50 ha)	C. Huidige situatie
Maatregel			
Waterkwaliteit	Water is helder en goede kwaliteit	Water is zeer helder en van zeer goede kwaliteit	Water is troebel en heeft een matige kwaliteit
Soortenrijkdom	gemiddeld, geen bedreigde soorten	hoog, met bedreigde soorten	laag
Toegankelijkheid	Overal bereikbaar via wandel/fietspaden	Beperkt bereikbaar via wandelpaden	Geen wandel/fietspaden
Extra watertaks per huishouden per jaar	10€/jaar	20€/jaar	0€

Figure D.1: One of the randomly generated choice cards presented to the respondents of the choice experiment survey. Respondents could either choose for the status quo without a tax increase or for a particular improvement of the conditions of the pond with an associated tax increase.

Appendix E

Table E.1: Experts consulted for model structure development.

Name	Function	Institute
Pieter Lemmens	Post-doctoral researcher	Laboratory of Aquatic Ecology, Evolution and Conservation, KU Leuven
Tom De Bie	Watershed policy officer	Flemish Environmental Agency
Steven Declerck	Researcher	Netherlands Institute for Ecology
Luc De Meester	Professor	Laboratory of Aquatic Ecology, Evolution and Conservation, KU Leuven

Table E.2: Experts consulted for model structure review and quantification of conditional probability distributions.

Name	Function	Institute
Mike Jeffries	Lecturer	Northumbria Universtiy Newcastle
Martijn Schiphouwer	Ecologist	Stichting RAVON
Gerald Louette	Ecologist	Research Institute for Nature and Forest
Guido Waajen	Ecologist	Dutch government administration
Jordie Netten	Consultant	Nelen and Schuurmans
Reinder Torenbeek	Consultant	Torenbeek Consultant
Roelf Pot	Consultant	Roelf Pot onderzoek- en adviesbureau
Ronald Bijkerk	Consultant	Koeman en Bijkerk bv
Tom De Bie	Watershed policy officer	Flemish Environmental Agency

Table E.3: Fish farmers consulted for quantification of conditional probability distributions.

Name	Company
Roger Vandeput	Viskwekerij Vandeput en Zonen
Dominiek Bijnens	Aquafarm
Anton Bijnens	Viskwekerij Sint Pieter

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Curriculum vitae

Personal information

Dries Landuyt was born in Herentals on the 2nd of December in 1988. He went to school in Vorselaar and completed his secondary education in 2006. The same year, he started his Bioscience Engineering studies at Ghent University. During his studies, he specialised in nature management, forestry and spatial analysis and wrote a master thesis on alternative wood species for the construction of violin bows, a work that focused on wood technology, wood anatomy and sustainable forestry. In 2011, he received his master degree in Bioscience Engineering with great distinction.

During his doctoral training program, Dries followed several courses on GIS techniques, modelling and programming. More specifically, he specialised in ecosystem service modelling, Bayesian belief networks and spatial application of Bayesian belief networks. During his PhD, he contributed to several projects, wrote several articles in peer-reviewed scientific journals, presented at several international conferences and contributed to several book chapters.

Education

2011 - 2015	Doctor in Applied Biological Sciences Ghent University
2009 - 2011	Master of Bioscience Engineering: Forest and Nature Management Ghent University
2006 - 2009	Bachelor of Bioscience Engineering: Land and Forest Management Ghent University
2000 - 2006	Secondary education, Science-Mathematics Kardinaal Van Roey Instituut Vorselaar

Publications

Articles in peer-reviewed scientific journals (A1)

Landuyt, D., Broekx, S., Goethals, P.L.M. (In Preparation). Bayesian belief networks to analyse trade-offs and synergies among ecosystem services at the regional scale. Ecological Indicators.

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Chapters in books

Van Echelpoel, W., Boets, P., Landuyt, D., Gobeyn, S., Everaert, G., ,Bennetsen, E., Mouton, A., Goethals, P.L.M., 2015. Species distribution models for sustainable ecosystem management. In Park, Y.-S., Lek, S., Baehr, C., Jorgensen, S.E. (Eds.), Advanced modelling techniques studying global changes in environmental sciences. Elsevier, San Diego. pp. 113-132

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Presentations

Oral presentations at national and international conferences

Van der Biest, K., Landuyt, D., Staes, J., Seynaeve, J., Goethals, P., Meire, P., 2015. Linking GIS with decision networks for ecosystem services based vision building. ESP Conference, Stellenbosch, South Africa

Bennetsen, E., Landuyt, D., Broekx, S., Goethals, P., 2015. Assessment of ecosystem services trade-offs resulting from land management choices with Bayesian belief networks. ESP Conference, Stellenbosch, South Africa

De Valck, J., Landuyt, D., Broekx, S., Liekens I., De Nocker, L., De Valck, K., Vranken, L., 2015. Outdoor recreation in various hypothetical landscapes: which site characteristic really matter? 17th Annual BIOECON Conference: Biodiversity, Ecosystem Services and Sustainability, Cambridge, United Kingdom

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Landuyt, D., Broekx, S., Van der Biest, K., Goethals, P.L.M., 2014. Probabilistic mapping with Bayesian belief networks: An application of ecosystem service delivery in Flanders, Belgium. 7th International Congress on Environmental Modelling and Software (iEMSs 2014), San Diego, California

Landuyt, D., Broekx, S., De Valck, J., De Nocker, L., Liekens, I., Goethals, P.L.M., 2013. Applying Bayesian belief networks and GIS to model the ecosystem service recreational use. 19th biennial conference of the International Society of Ecological Modelling (ISEM 2013), Toulouse, France

Staes, J., Van der Biest, K., Landuyt, D., Broekx, S., Goethals, P.L.M., Meire, P., 2013. Bayesian belief networks as a supportive tool for landscape planning - a case study in the Belgian landdune region. ESP conference 2013, Bali, Indonesia

Bennetsen, E., Landuyt, D., D'hondt, R., Goethals, P.L.M., 2013. Strengths and opportunities of Bayesian Belief Networks for decision making in urban watersheds:

insights from a case study in Port of Ghent, Belgium. SURE 2013, Berlin, Germany

Landuyt, D., Broekx, S., Goethals, P.L.M., 2013. Kennisintegratie en conceptuele modellering van ecosysteemdiensten. ECOPLAN event, Antwerp, Belgium

Van der Biest, K., D'hondt, R., Jacobs, S., Landuyt, D., Staes, J., Meire, P., Goethals; P.L.M., 2013. An integrated model to assess the effects of land use change on the delivery of multiple ecosystem services. Ecosystem service workshop 2013, Kiel, Germany

Landuyt, D., Bennetsen, E., D'hondt, R., Engelen, G., Broekx, S., Goethals, P.L.M., 2012. Modelling ecosystem services using BBNs: Burggravenstroom case study. 6th International Congress on Environmental Modelling and Software (iEMSs 2012), Leipzig, Germany

D'hondt, R., Landuyt, D., Van der Biest , K., Jacobs, S., 2012. Determination of trade-offs in ecosystem service delivery using Bayesian belief networks. 21th Belgian-Dutch conference on machine learning, Ghent, Belgium

Poster presentations at national and international conferences

Forio, M.A.E., Landuyt, D., Bennetsen, E., Boets, P., Goethals, P.L.M., 2015. Bayesian belief networks to support decision making in river basin restoration. REFORM International Conference on River and Stream Restoration: Novel Approaches to Assess and Rehabilitate Modified Rivers, Wageningen, The Netherlands

Landuyt, D., 2014. PMAT: A Quantum GIS plug-in to support the use of Bayesian belief networks in ecosystem service delivery mapping. BEES Christmas market 2014, Gembloux, Belgium

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Vangansbeke, P., Landuyt, D., 2014. Integration of Ecosystem Services in Bosland. BEES Christmas market 2014, Gembloux, Belgium

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Educational activities

Guest lectures

Landuyt, D., Bennetsen, E., 2013. Ecosystem services - Assessing the value of a good water status. Ghent, Belgium

Landuyt, D., D'hondt, R., 2012. Ecosystem services - Integrating natural capital in decision making. Ghent, Belgium

Tutor of master thesis students

Quinten Cormenier (2014-2015). Ruimtelijk modelleren van ecosysteemdiensten aan de hand van Bayesian belief networks. Ghent University.

Minar Naomi Damanik Ambarita (2012-2013). Monitoring and modelling of the ecological water quality of the Cuenca rivers in Ecuador. Ghent University.